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Sentiment-Apt investors and UK sector returns

Rilwan Sakariyahu[1] | **Mohamed Sherif**[1] | **Audrey Paterson**[2] | **Eleni Chatzivgeri**[1]

[1]Edinburgh Business School, Heriot-Watt University, Edinburgh, UK

[2]Business School, University of Aberdeen, UK

Correspondence
Mohamed Sherif, Edinburgh Business School, Heriot-Watt University, Edinburgh, EH14 4AS, UK.
Email: m.sherif@hw.ac.uk

Abstract

This paper examines the relationship between sentiment-apt investors and UK stock returns at industry level over the period January 1988 to December 2017. Using two new sentiment proxies (laggards to leaders and growth opportunity index) for 10 discrete sector groupings, we provide novel evidence on how returns in the UK stock market react to the activities of sentiment-disposed investors. First, using threshold nonlinear regression, we document a significant relationship between the laggards to leaders sentiment proxy and sectoral returns. Our findings reveal that aggregate returns in the sector are affected by activities of investors who embark on profit-taking when there is an increase in the proportion of lagging to leading stocks beyond the threshold value. Secondly, when using the growth opportunity sentiment proxy, we report that the increase in growth above the growth threshold value has a significant impact on sector returns. This study further confirms significant impact of non-threshold variables on sector groupings. Our findings are robust, having been subjected to a range of robustness checks.

KEYWORDS

growth opportunity, investor sentiment, laggards to leading, UK

1 | INTRODUCTION

For several decades, the efficient market hypothesis (EMH) stood as the dominant theoretical framework for capital market analysis. Across financial markets in the world, the development of financial policies, strategies and price modelling was centred on the assumptions of market efficiency. In recent times however, this notion has faced several theoretical and empirical criticisms, arising from observed flaws in its adaptation (Barber and Odean, 2007; Kim and Kim, 2014; Chen and Sherif, 2016; Gârleanu and Pedersen, 2018).[1] Consequently, the emergence and development of behavioural finance has become a centre of discourse in the financial literature.

Behavioural finance posits that stock price movements reflect psychological processes of market participants and the information structure around financial markets, which systematically influence investors' attitude and perception towards the market (Shefrin and Statman, 2000). Nevertheless, stock markets around the world are designed in such a way as to attain efficiency, whether at the weak, semi-strong or strong form (Malkiel and Fama, 1970; Sherif and Chen, 2019), so that no individual or institutional investor can consistently outperform the average expected performance of the market due to past, private or publicly available information. However, a large body of empirical evidence has shown that sentiments significantly account for the frequent movements in stock prices, as investors are described as being generally discerning about financial investments (Fisher and Statman, 2003; Baker and Wurgler, 2006; Schmeling, 2009; Arin et al., 2013; Yang et al., 2017; Uhl, 2014).

Compared to the incongruous proxies adopted by previous works, our study, in two different ways, provides new evidence on how activities of sentiment-induced investors shape aggregate stock returns at the industry level. First, using UK sector-based data between January 1988 and December 2017, we examine both the ratio of lagging to leading stocks, and also the growth opportunity index, as proxies for sentiments. Secondly, we analyse the impact of both variables on sectoral returns using both linear and non-linear approaches. Our choice of the UK market is due to its strategic importance in the world financial markets generally, and in that of Europe, in particular. With a market capitalization of almost five trillion dollars as at April 2018 (LSE quarterly report, 2018), the UK market is, the largest market in Europe, and is undoubtedly an attractive investment platform for prospective investors who crave for optimum returns and diversification. Given its global pertinence, market depth and perhaps efficiency, we strongly advocate that sentiments should not drive sectoral returns in the UK stock market. Moreover, the wave of uncertainties regarding the future of the UK economy due to its proposed exit from the European Union (Brexit) is another motivation for this study.

Again, our choice of sentiment variables stems from the assumption that sentiment-prone investors are mostly risk-averse investors who are generally more concerned about loss minimization than return maximization (Shefrin and Statman, 2000). Hence, we hypothesize that for any given sector or industry, when the ratio of underperforming to over-performing stocks is consistently increasing (i.e., ratio of laggards to leaders), sentiment-apt investors would gradually avoid such sectors, and consequently, overall return index of the sector would be negatively affected. In addition, we hypothesize that although investors have disparate attitudes towards each sector of the stock market, rational investors are nevertheless allured and thus converge towards sector(s) with growth potential. By implication, such sectors exert influence on market sentiments and in turn, create a significant impact on the overall sectoral return index. A graphical representation of variables used for this study is shown in Figures 1 and 2.[2]

Over the years, the behavioural strand of finance has been advanced by several studies on sentiments and returns, with an array of proxies for sentiment and a major emphasis on aggregate market returns. However, the inconsistent and varied positions of prior studies have exacerbated the debate on market sentiments in the financial literature. For instance, proponents of media-based sentiment provide logical arguments to support the belief that threads on social media stimulate the attitude of investors towards the market which consequently affect stock price movement (Bollen et al., 2011; Rao and Srivastava, 2012; Oliveira et al., 2013; Mostafa, 2013; Nofer and Hinz, 2015; Leitch and Sherif, 2017). These studies conjecture that market sentiment is attributed to the sensitivity of investors who rely on information sourced from popular print and online media outlets (such as Yahoo-Finance, Google, Twitter, Wall Street Journal, New York Times and Financial Times). Hence, they conclude that the propensity of such information channels to induce price fluctuation is significant. However, the findings of these studies have been discredited based on the notoriety of media fake news and the reality that the influence of information contained in media outlets largely depends on the number of positive or negative words, the popularity of the media outlets and the commenter.

Furthermore, another group of sentiment studies support the use of consumer surveys as proxies for sentiments (David and Sultan, 1998; Jansen and Nahuis, 2003; Arabian and Zomorrodian, 2007; Chen, 2011; Salhin et al., 2016; Brown and Cliff, 2005; Yang et al., 2017). These studies opine that consumer surveys significantly highlight respondents' financial and socio-economic status and, in addition, evaluate investors' optimism on future expectations of the economy. However, information obtained from surveys cannot be sufficiently trusted, considering that scant, dishonest and misleading information may be provided by respondents, which consequently inhibits the predictive power of surveys (Singer, 2002; Schmeling, 2009).

In the spirit of the above sentiment conundrum and in light of the increasing scepticism due to indecisions regarding Brexit plans, our study bridges the gap in the literature by providing clarity, new factual findings and precautionary information for market regulators, investment professionals, academics, policy makers and also in relation to the general investment environment regarding the vulnerability of UK sectoral returns to the activities of sentiment-induced investors.

The remainder of this paper is structured as follows. Section 2 provides a literature review of studies that have considered the Fundamental (Economic) Determinants of Stock Market Returns and Sentiment-based Determinants of Stock Market Returns, in order to support the formulation of our hypotheses. Section 3 provides details of the data and methodology. Section 4 presents the empirical findings, and Section 5 concludes the paper, stating the significance of the main findings and outlining avenues for future research.

2 | CONTEXTUALIZATION OF THE STUDY

Although the basic consensus in the literature suggests that markets behave randomly, it is, nonetheless,

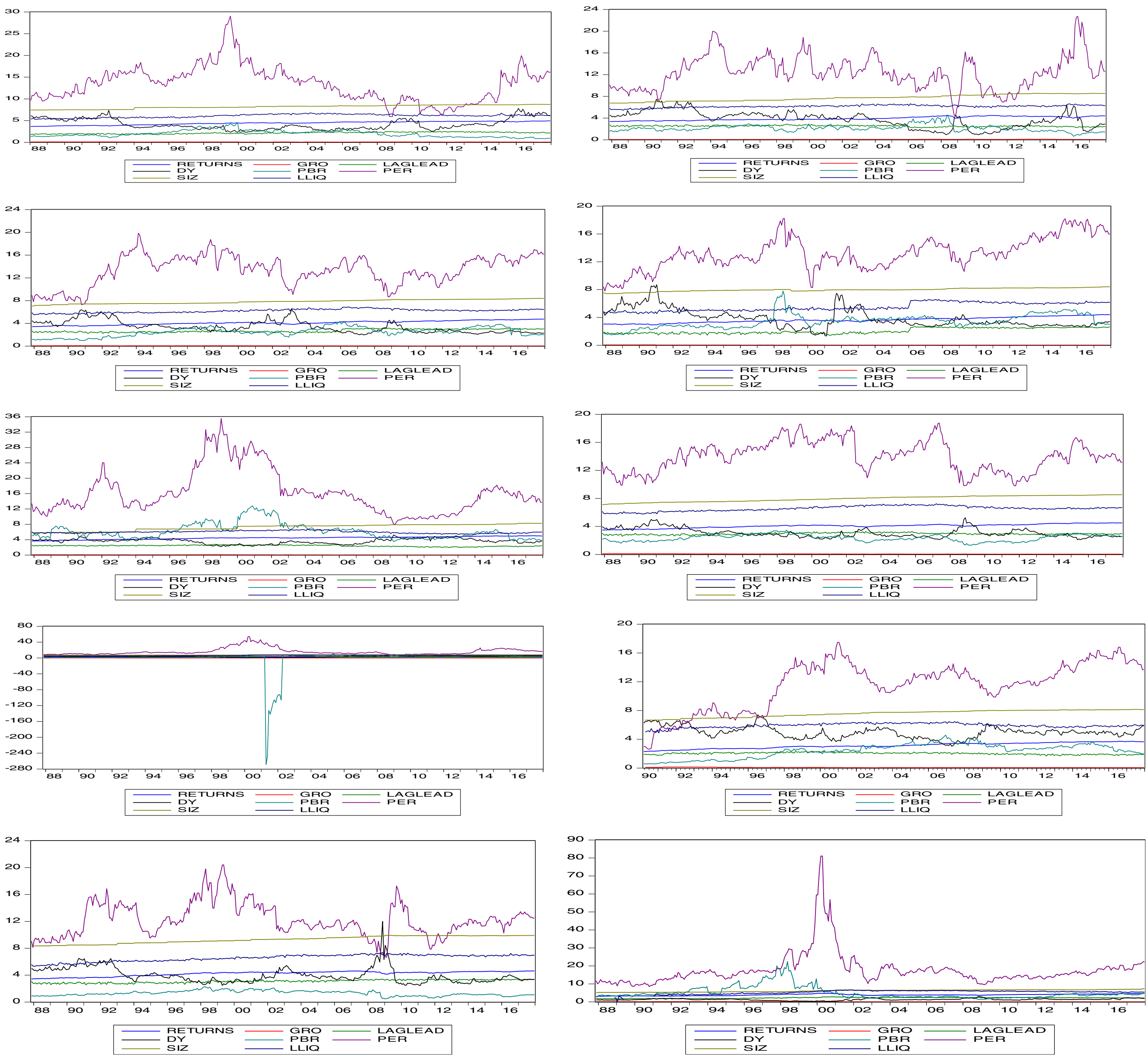

FIGURE 1 Sector groupings returns [Colour figure can be viewed at wileyonlinelibrary.com]

imperative to highlight that a multitude of approaches have been suggested by previous studies to account for the sharp or gradual change in prices of stocks across sectors or markets. The behaviour of each market is akin to response to stimuli; that is, its perception and reaction to activities of both internal and external environments. Analysing market behaviour involves identifying factors affecting risk and returns in the market. In the literature, such factors are grouped into two categories: fundamental and sentiment factors. Empirical studies into these factors are discussed in the next subsection.

2.1 | Fundamental (economic) determinants of stock market returns

As an extension to the capital asset pricing model (CAPM) earlier introduced by Sharpe (1964), Ross's (1976) theory of arbitrage pricing (APT), laid, arguably, the most prominent foundation for most studies investigating the influence of economic variables on market behaviour. CAPM recognizes the role of an asset's systematic risk (as represented by beta) in predicting its expected return. In contrast, APT advocates that the behaviour of an asset is a linear function of macroeconomic factors whose

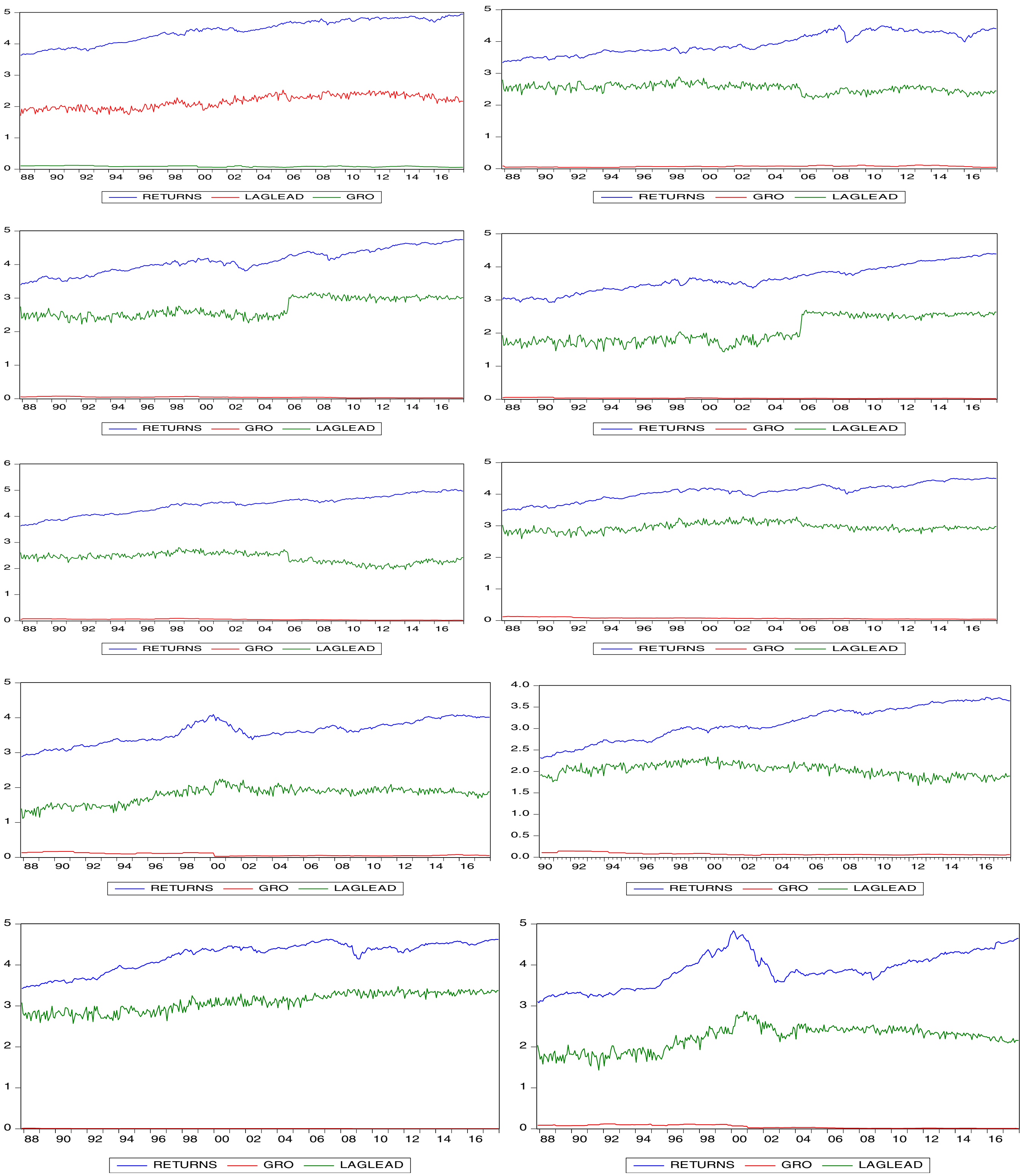

FIGURE 2 Sentiment indicators and sector groupings returns [Colour figure can be viewed at wileyonlinelibrary.com]

number and nature change periodically and between economies. Providing empirical explanations to the nature of macroeconomic factors that affect markets, Chen et al. (1986) identify surprises in inflation and gross national product as key variables.

The APT's ability to predict stock return provides strong footing for many of the earliest empirical works on stock market behaviour; consequently, subsequent studies have adopted factor analysis in identifying significant economic variables, whether for a country study or a cross-country endeavour. For example, Kearney and Daly (1998) investigate the causes of stock price fluctuations in Australian stock market. Employing Generalized Least Squares (GLS) estimation strategy to analyse monthly data, the study observes that macroeconomic variables such as inflation and interest rates are direct determinants of volatility in Australian stock market while industrial production, money supply and current account deficit have indirect impact on stock market volatility. Among the variables adopted in the study, money supply is observed to have the strongest effect on stock price movements in Australia. In another study, Flannery and Protopapadakis (2002), using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and U.S. daily equity returns, find that consumer price index, monetary aggregate, purchasing power index, balance of trade, employment report and housing statistics have a significant impact on aggregate stock returns in the U.S. In a related study in New Zealand, although with a different methodology, Lee and Gan (2006) examine the effect of macroeconomic variables (such as consumer price index [CPI], long term interest rate, short term interest rate, real GDP, exchange rate, money supply and domestic retail oil prices) on the NZSE Index between January 1990 to January 2003. With the aid of Johansen multivariate co-integration tests and Granger causality tests, Lee and Gan (2006) find that all macroeconomic variables adopted (except exchange rate and inflation rate index) have a significant impact on NZSE Index.

In another study providing evidence for cross-country analysis, Garcia and Liu (1999) investigated the macroeconomic determinants of stock market development using pooled data from 15 industrial[3] and developing countries from 1980 to 1995. Their study shows that savings rate, real income and liquidity are important determinants of stock market development in those countries. Similarly, Errunza and Hogan (1998) investigated the impact of macroeconomic data on European stock market volatility. Their study showed that past variability of monetary or real macroeconomic factors have significant impact on stock market volatility within Europe. In other work, using markets in Latin America, Errunza and Hogan (1998) examined the relationship between macroeconomic volatility and stock returns, and found that macroeconomic indicators such as interest rates, industrial production, money supply, MSCI world index, U.S. 3-month T-bill yield and exchange rates are consistently significant in explaining returns across all markets, although at varying significance and magnitudes. Further, using co-integration analysis, Humpe and Macmillan (2009) document influence of macroeconomic variables on stock prices in U.S. and Japan. They report that in the U.S., stock prices are influenced positively by industrial production and money supply but have negative relationship with CPI and long term interest rate. For the Japanese market on the other hand, their study finds that stock prices are negatively influenced by money supply but positively by industrial production.

Evidence of macroeconomic variables influencing stock price behaviour has also been documented in the emerging markets. For instance, in the case of European emerging markets, using data from 1990 to 1999, Patra and Poshakwale (2006) explore the effect of fundamental variables on stock returns in Greece. Adopting a Granger causality, co-integration test and error correction model, their study demonstrates that inflation, money supply and trading volume have both short and long run relationships with prices of stocks in Greece, although the exchange rate has no co-integrating relationship with stock prices. Similarly, providing evidence of fundamental factors in Turkey stock market returns, Kasman et al. (2011) investigate the effects of changes in interest rates and foreign exchange rates on banks' stock returns and, found that both interest and exchange rates are major determinants of banks conditional returns, owing to their significant negative impacts.

Shifting attention to emerging markets in Africa, Yaya and Shittu (2010) examined the impact of inflation and exchange rate on conditional stock market volatility in Nigeria. Using a QGARCH model, the study shows that previous exchange rates and inflation rates have significant effects on conditional stock market volatility. In the same vein, Olweny and Omondi (2011) examine the impact of macroeconomic indicators on stock market volatility in Kenya using data from January 2001 to December 2010. Applying EGARCH and TGARCH models, their study reveals that volatility in Kenya is largely influenced by interest rate, inflation rate and exchange rate. Elsewhere, Hsing (2011) explores the impact of macroeconomic factors on the stock price behaviour in South Africa. With the use of exponential GARCH model, Hsing (2011) finds that the growth rate of real GDP, the ratio of money supply to GDP and the U.S. stock market index have a positive impact on South African stock returns, whereas government deficit to GDP, domestic real interest rate, nominal effective exchange rate, U.S. government bond yield and domestic inflation rate have a negative impact on stock returns.

With regard to emerging markets in Asia, Patel (2012) explores the influence of macroeconomic variables on Indian stock market returns between January 1991 and December 2011. Adopting Vector Error Correction Model (VECM), Patel (2012) shows that all macroeconomic variables adopted in the study are major determinants of stock price behaviour in India. Similarly, Zakaria and

Shamsuddin (2012) provide empirical evidence on the impact of macroeconomic volatility on stock market volatility in Malaysia. Using GARCH model and VAR Granger causality to estimate volatilities of inflation, exchange rate, GDP, interest rates and money supply between January 2000 and June 2012, their study finds that all macroeconomic variables (except inflation) provide insignificant evidence of causality on the Malaysian stock market. Most recently, Ahmadi (2016) evaluates the effects of two macroeconomic variables, namely, output growth and inflation, on real stock returns and volatility of the Tehran Stock Exchange. Using EGARCH model, the study breaks the sample period (2005–2014) into sub-samples, thus accounting for major crises in the Iranian economy. Ahmadi (2016) demonstrates that both output growth and real stock returns largely determine stock volatility in Iran during the sub-periods. However, no significant evidence of effect was found when the whole period was considered.

2.2 | Sentiment-Based determinants of stock returns

The appropriateness (or otherwise) of macroeconomic fundamentals in explaining stock price behaviour is tainted by the plethora of recent behavioural finance studies providing convincing evidence and empirical alternatives. The behavioural strand of research focuses on market sentiments and has enjoyed, on the one hand, large support from the psychological evidence of cognitive illusions in decision making and, on the other hand, a myriad of empirical evidences. Sentiments, or in broad terms, behavioural finance, suggest that investors react to expected price development in the market by engaging in complex cognitive assessment of fundamental, technical and non-fundamental factors peculiar to the market. An assessment of these factors, to a large extent, influences investors' choice of stock (or portfolio) and has the potential to alter the stance of classical market theories (Shefrin and Statman, 2000). However, although many studies in the literature have documented both linear (Edmans et al., 2007; Akansu et al., 2017) and non-linear relationships (Bollen et al., 2011; Essaddam and Karagianis, 2014; Chu et al., 2016; Salhin et al., 2016; Bekiros et al., 2016; Yang et al., 2017) between stock market behaviour and sentiments, the controversy still lingers due to multifarious and imperfect proxies for market sentiments.[4]

Furthermore, an array of theories has been proposed in the financial literature to substantiate sentiments and stock price return. For instance, Tinbergen (1939) propounded the adaptive expectation theory, Simon (1955) proposed the bounded-rational theory, Tversky and Kahneman (1981) advocated the prospect theory, Merton (1987) introduced the investor recognition hypothesis, Epstein (1999) explored the ambiguity aversion theory, and Shefrin and Statman (2000) proposed the behavioural portfolio theory. The underpinning argument of these theories is that stock prices are not solely affected by fundamental indices. Rather, the activities of noise traders also provide justification for human sentiments that drive market fluctuations. Accordingly, a growing number of studies have adopted different proxies to measure sentiments; these proxies are categorized as market-based, media-based, internet-based, non-fundamental and survey-based sentiment measures.

2.2.1 | Market-Based sentiment measures

A variety of financial market-based proxies have been used to establish a link between investors' sentiments and stock market behaviour. Using trade volume, while some studies in developed markets report a positive relationship with market returns, other studies in emerging markets have documented a negative relationship between trading volume and market returns. For example, Gervais et al. (2001)'s study on the U.S. market, and also similar studies in different countries (Chordia et al., 2001; Gagnon and Karolyi, 2009; Chandra Pati and Rajib, 2010; Chen, 2012), all find a significant positive relationship between trading volume and return. Conversely, other studies, such as Lee and Rui (2000, 2002); Bohl and Henke (2003); Girard and Biswas (2007); Chiang et al. (2010), document a negative relationship between trading volume and market returns.

Additionally, a few studies also adopt extreme 1-day return to measure market-based sentiment. For instance, Cox and Peterson (1994), Larson and Madura (2003) and Barber and Odean (2007), all found a significant influence of extreme day return on price behaviour. Furthermore, a strand of research has focused on predictability of price behaviour using the â€˜investors fear gauge' as measured by both the Credit Suisse Fear Barometer (CSFB) and the Chicago Board Options Exchange Volatility Index (CBOE VIX). In their respective findings, Brown and Cliff (2004); Baker and Wurgler (2007); Smales (2014); Freybote and Seagraves (2017) and Campbell et al. (2018) among others, suggest that these two measures are appropriate proxies for investors' sentiment. Similarly, Ben-Rephael et al. (2012) investigate investors' sentiment using mutual funds flow and reveal its significant correlation with stock returns. Baker and Stein (2004) adopt market liquidity as a proxy for sentiment by examining and reporting significant impact of bid and ask spread on aggregate market returns. Kang et al. (2002), Cooper et al. (2004), Bandopadhyaya and Jones (2006), Antoniou et al. (2013) and a host of other studies explain investors' sentiment and stock market returns using price momentum. Furthermore, Lee et al. (1991), Chen et al. (1993), Chopra et al. (1993), Lowry (2003) and Doukas and Milonas (2004) demonstrate that discounts (or premium) on closed-end funds are as a useful factor in measuring the correlation between stock returns and investor sentiment. In the same vein, Baker and Wurgler (2004), Simões Vieira (2011) and Feldman (2010) find dividend premium as an adequate proxy of investor sentiment. They find that investors express sentiment towards average book-to-market ratio of companies paying dividends and also to those not paying. Furthermore, using IPO as a proxy for investor sentiment, Lee et al. (1991), Cornelli et al. (2006), Baker and Wurgler (2007), Dorn (2009), Finter et al. (2012) and Jiang and Li (2013), among others, find first day returns and the volume of IPO to be a significant barometer for investor sentiment.

2.2.2 | Media-Based sentiment measures

In another stream of research, protagonists of market sentiments propose the tracking and extraction of investors' moods from social media networks and print materials (such as blogs, Facebook, Twitter, magazines, news networks and other relevant finance-related media sources). A significant number of studies report that threads on social media can reflect, on the one hand, the attitude of investors towards the market and, on the other hand, investors' perceptions towards the general state of the economy. Using twitter, Oliveira et al. (2013) indicate in their study that the sentiment of stock-tweets has the potential to predict stock market liquidity although with little predictive power on return predictability. Providing a robust explanation of the impact of tweet sentiments, Rao and Srivastava (2012) analysed more than four million tweets in a bid to examine the relationship between the sentiments of board tweet and financial market reactions. Employing the Granger causality test, the study constructed a special mood tracking measure to differentiate positive from negative tweets, and concluded that a strong positive correlation exists between board tweets and stock price behaviour. Other studies (Bollen et al., 2011; Zhang et al., 2011; Rao and Srivastava, 2012; Mostafa, 2013; Nofer and Hinz, 2015; Ranco et al., 2015; Zhang et al., 2017) also find varying degrees of significant relationship between twitter posts and stock price behaviour.

From another perspective, O'Connor (2013) investigates the correlation between Facebook posts and the stock price behaviour of companies. Using a sample of the 30 most popular consumer brands in the U.S., the study identifies a high correlation between socio-behavioural indicators of brands and their price performances in the market. Likewise, constructing a Facebook Gross National Happiness (GNH) measure, Siganos et al. (2014) findings corroborate the findings of the above study on Facebook sentiments by reporting a positive contemporaneous relationship between investor sentiments and stock returns.

In another vein, assessing the impact of articles in magazines and popular financial newspapers (such as Financial times, New York Times or Wall Street Journal) on stock price movement, Barber and Odean (2007), Dougal et al. (2012) and Ahern and Sosyura (2015) establish a varying significant effect of information published in these financial outlets on stock returns. Similarly, Uhl (2014) examined the propensity of sentiments from more than 3.6 million Reuters' news articles to predict returns of the Dow Jones Industrial Average stock index. Using a vector auto-regression model, Uhl (2014) showed that negative sentiments derived from Reuters provide better explanation to stock returns than macroeconomic factors.

To conclude, the importance of the above media-related sentiments cannot be under-estimated given the empirical weight espoused in these findings. However, the arduous task involved in the mining of such types of data, as well as the special analytical processes required in the transformation and interpretation, make the use of media-based data less feasible.

2.2.3 | Internet-Based sentiment measures

Akin to media-related sentiments is the use of online search facilities to gather relevant information about stocks and their behaviour over time. In particular, to consider the popular use of Investopedia, Google and Yahoo (Finance) search engines to generate facts about stocks, sector or aggregate market. Some studies have demonstrated the pertinence of results generated from such online searches on the attitudes of investors towards returns, volatility and trading volume. For instance, using a sample of 189 "Google-searched" stocks between 2008 and 2011, Takeda and Wakao (2014) found a positive relationship among trading volume, stock returns and Google online searches in the Japanese market. Their results suggest that increased search activity is strongly correlated with increased volume, but that the impact on stock returns is significantly weak. In another study, Bordino et al. (2014) examined the relationship between stock trading and web browsing using messages posted on the Yahoo (Finance) message board. Using more than 2,600 stocks, their study reveals that web browsing on the Yahoo (Finance) has predictive power on overall stock trading volumes, although this is at a decreasing rate when the stocks are grouped into industries or sectors. Providing a different view however, Kim and Kim (2014) used over 32 million messages posted on the Yahoo (Finance) message board regarding 92 firms, extracted between 2005 and 2010, and found no evidence of predictability of trading volume, volatility and stock returns, whether at firm or aggregate level. However, their study finds significant evidence that stock price performance positively affects investor sentiments. Other related studies (Sehgal and Song, 2007; Drake et al., 2012; Preis et al., 2013; Da et al., 2014; Zhang et al., 2017) also affirm the impact of Google and Yahoo online searches on trading patterns and stock behaviour.

2.2.4 | Non-Fundamental sentiment measures

Interestingly, the literature has witnessed an array of studies documenting the role of non-fundamental, or perhaps, non-economic events, on market behaviour. Authors of such studies argue that events such as aviation disasters, sports competitions, health outbreaks, politics and weather, influence investors' risk disposition towards investment decisions. For instance, documenting the influence of sports on returns, Edmans et al. (2007) report a significant correlation between match outcomes and market returns. Using a cross-section of 39 countries, their findings show that stock markets of match losing countries suffer abnormal decline (of about −0.50%) a day after a major international match is lost and such decline is suffered particularly by small-stock companies. Their study, however, finds no evidence of correlation between stock returns and match victories. Corroborating the findings of Edmans et al. (2007), Scholtens and Peenstra (2009) find significant and positive next-day returns for match victories and stronger negative returns for match defeats. Meanwhile, from a firm-level point of view, Chang et al. (2012) also find a significant next-day decline in stocks of firms that are geographically located near a losing National Football League team. In fact, they reveal that the magnitude of decline in such stocks' returns is significantly influenced by an unexpected loss in important games.

Providing evidence for a weather-effect, Hirshleifer and Shumway (2003) deploy a sample of 26 countries to investigate the relationship between morning sunshine and market returns, from 1982 to 1997. As humorous as it may first appear, the authors in their wisdom nevertheless provide an intuitive revelation on how stock returns are significantly correlated with morning sunshine, but uncorrelated with snow and rain. Hence, the study creates a weather-based trading strategy for both itinerant and agriculture-inclined traders, desirous of low transaction costs and optimum gains. Supporting this argument, Goetzmann et al. (2014) also detail significant correlation between the weather-induced mood of investors and stock returns. From a gender-based sentiment perspective, Wolfers (2006) explored the influence of CEO gender on stock returns over the period 1992–2004. Using a sample of 1,500 firms, Wolfers (2006) reports no systematic differences in returns of stocks, whether headed by a male or a female. Chen (2007) assessed the effect of both fundamental and sentiment indices on stock returns in China. To proxy sentiments, the study adopted events such as the United States 9/11 terrorist attacks, the Sydney 2000 Olympics, the Asian financial crisis and the SARS outbreak. The outcome of Chen (2007) study shows that the sentiment indices have a significant negative effect on stock returns in China.

The evidence of an air pollution-effect on stock returns is also demonstrated in the work by Levy and Yagil (2011). Drawing on data from four stock exchanges in the U.S. and the Air Quality Index, their study demonstrates that stock returns are significantly negatively impacted by air pollution, particularly for those firms located near to the pollution area. The finding of the study thus provides a trading strategy for environmental-conscious investors and firms, particularly industrial and manufacturing firms that emit waste substances into the ecosystem.

From the above studies, it is clear that the use of non-fundamental factors as proxy for sentiments is well documented in literature. Caution is, however, necessary for their adoption as non-fundamental factors are often solitary events, with no direct connection to stocks; thus, proposing an empirical relationship between such factors and stock returns may require a leap of faith from the readers or audience.

2.2.5 | Survey-Based sentiment measure

In lieu of the inconsistent sundry measures for market sentiments, some studies generate sentiment indicators through surveys, either by directly administering questionnaires to relevant respondents or by extracting survey responses from existing databases. While some survey questions are open-ended, others restrict respondents to pre-designed responses (i.e., close-ended). Regardless of the restrictions they impose on respondents, close-ended surveys have enjoyed widespread adoption in studies. A popular instrument of survey-based sentiment measure is the consumer confidence-sentiment index, computed by the University of Michigan. This index largely addresses investors' optimism on future expectations of the economy, and also highlights issues pertaining to the respondents' financial and socio-economic conditions (Brown and Cliff, 2005). Despite considerable usage of this index, however, its susceptibility to dishonest and sparse information inhibits its predictive power regarding market behaviour, thus leading to conflicting outcomes in the literature (Singer, 2002; Schmeling, 2009).

While some authors report a significant positive relationship between market returns and investors sentiment (measured by consumer confidence index), others have outlined a significant negative relationship. For example, David and Sultan (1998) investigated the link between consumer confidence and financial market response between 1980 and 1993. Their assessment of the effect of consumer confidence on the conditional mean and volatility of stock, bond and foreign exchange prices shows that consumer confidence has a significant asymmetric impact on the conditional mean of all sampled countries, but not on their conditional volatilities. Using data for 11 European countries between 1986 and 2001, Jansen and Nahuis (2003) investigated the short run link between consumer confidence and stock market developments. With the aid of Granger causality, the study observes a positive causal relationship between changes in sentiments and stock returns of nine countries except for Germany. In other work, adopting a Markov-switching approach, Chen (2011) examined the relationship between stock returns and confidence level of consumers during fluctuations in the U.S. market. Chen (2011) also finds that a positive relationship exists between confidence level and stock market returns, such that when there is decreased confidence, markets move into a bear territory. Elsewhere, using vector auto-regression to analyse weekly survey data in Germany, Lux (2011) observes that a causal relationship between investors' mood and subsequent stock price changes can only be established when the time frame is taken into consideration; that is short, medium or long run. In a similar study in Germany, Finter et al. (2012) use a principal component analysis to develop investor sentiment indicators to examine whether these indicators explain stock market returns in Germany. Their study records that the indicators explain the return spread between sentiment-sensitive and non-sentiment-sensitive stocks. Furthermore, their study observes that sentiment has little predictive power on expected returns in Germany. Similarly, Chung et al. (2012) also examine the impact of asymmetric sentiments on cross-sectional stock returns with different regimes. Using business cycles from the National Bureau of Economic Research (NBER) to segregate economic states, and through adopting a multivariate Markov regime-switching model, their study reveals that investor sentiment is often related to expansionary regimes, which in turn lead to high stock returns. However, their study details only an insignificant predictive power of sentiment on stock returns during a state of recession. In other work, Corredor et al. (2013) explore the relationship between stock returns and investor sentiment in European markets. Their study finds that future stock returns are positively affected by investor sentiment, although with varying significant levels across the sampled countries.

As noted above, other studies have also delineated a negative relationship between consumer confidence and stock returns. Fisher and Statman (2000) suggest a statistically significant negative relationship between changes in investor sentiment and subsequent stock returns. Their work reveals that low consumer confidence is followed by positive high returns in the market. Also, Lemmon and Portniaguina (2006) examine the relationship between consumer confidence and small-stock premiums in the U.S. Using data spanning the period 1956 to 2002, their study reports that sentiment does not predict changes in small-stock premium and momentum. In other work, Schmeling (2009) explored the link between investor sentiments and expected stock returns in 18 countries. Schmeling (2009) reveals a negative impact of sentiments on stock market returns across the sampled countries. Employing a cross-sectional approach, Schmeling (2009) provides evidence to show that future expected returns are low when sentiment is high, and vice versa. In the South African market, Dalika (2014) investigated the relationship between investor sentiment and stock returns by constructing proxies for investor sentiment for the period 1999 to 2009. Dalika (2014) results show that investor sentiment has a significant negative relationship with stock market returns for South Africa; such that returns are high when sentiment is low.

In a more recent study, Salhin et al. (2016) explored the link among managerial confidence, investor confidence and stock returns in the UK between 1985 and 2014. Their study finds that consumer confidence does not affect stock returns in the UK, while managerial sentiment has a significant impact on both sector and aggregate returns.

Other related studies have also documented consumer confidence from different viewpoints, apart from stock return. For example, Arabian and Zomorrodian (2007) explore the link between consumer confidence and economic fluctuations using quarterly data from the U.S. between 1980 and 2005. Although their Granger causality result shows that consumer confidence indices do not Granger-cause GDP and vice versa, the forecast variance decomposition, however, reveals a significant prediction of GDP by the variables adopted. In addition, Zouaoui et al. (2011) investigated the power of consumer confidence indicators to predict financial crises using a panel of 16 international stock markets. Their study outlines two major findings: first, investor sentiment has more impact on stock market returns in countries that have a low market integrity and institutional involvement. Secondly, their study also discloses that investor sentiment has the potential to create stock market crises. Finally, Ferrer et al. (2016) examined the relationship between consumer confidence indices and stock market meltdowns, using the dotcom and recent global financial crises. Their findings suggest that it is not always the case that consumer confidence will be positively related to expected stock market returns.

From the above review, it is evident that previous studies have adopted several proxies for sentiment and the resulting outcomes have been varied. In this present study, we contribute to the literature in two novel ways. First, we introduce new alternative variables (ratio of laggards to leaders and growth opportunity index) to capture sentiments, and secondly, we estimate the impact of these variables on returns from both linear and nonlinear approaches, using sector-based data.

3 | MODELS AND METHODOLOGY

The analysis in this study is based on both linear and non-linear regression models. The functional form of the linear regression is expressed as follows:

$$R_{i_t} = \left[\alpha + \sum_{n=i}^{m} \beta_n Y_{t-n} + \epsilon_{i_t}\right] \tag{1}$$

Where R_{i_t} is sectoral return index at different time periods, m is the maximal lag, Y_t symbolizes a vector of explanatory variables at different time periods and ϵ_t is the error or disturbance term. Following McMillan (2001), for each of the regressors, we begin with a lag length of five and systematically, we eliminate the lags as they become statistically significant based on the information criteria, hence eventually retaining their contemporaneous form.

Furthermore, we employ a threshold regression model in explaining sectoral returns using as threshold variables, separately, the ratio of laggards to leaders and the growth opportunity rate. Both threshold variables are denoted as $q1$ and $q2$ respectively in model 2 below. Regarding the origins of our approach, Tong (1978) and Tong and Lim (1980) introduced the threshold regression model as a form of time series model capturing the effect of changes in behavioural patterns of explanatory variables on the predicted variable. Hansen (1999) later developed this model to account for non-dynamism in model specification. The threshold regression model is a nonlinear model, which addresses the inherent flaws associated with the use of a linear regression model. Thus, the model considers both asymmetric effects and also possible shifts in relationships, the latter being peculiar features of business and economic variables. In a threshold regression model, predictors are associated with the outcome in a threshold-dependent way. The inclusion of a threshold parameter (the change point) allows threshold models to estimate nonlinear relationships between the dependent and independent variables, with almost complete accuracy. However, before adopting the threshold model, we deemed it necessary to ascertain the presence of linearity or nonlinearity in the data by using a graph to depict the relationship between the sectoral return and the two sentiment variables. This is in line with prior studies such as McMillan (2001) and Huang et al. (2008). The threshold regression models have the following functional forms:

$$R_{i_t} = [\beta_0 + \beta_1 Y_t (I(q1,2 \geq \nu 1,2)) + \epsilon_{i_t}] \tag{2}$$

Alternatively, Equation 2 can be written as

$$R_j = \left\{ \begin{array}{ll} \beta_0 + \beta_1 Y_t + \epsilon_{i_t}, & q1,2 \geq \nu 1,2 \\ \beta_0 + \beta_1 Y_t + \epsilon_{i_t}, & q1,2 < \nu 1,2 \end{array} \right\} \tag{3}$$

We replace Equation 3 as follows:

$$\boldsymbol{R_t \nu}(1,2) = \begin{pmatrix} \boldsymbol{Y}_t(\boldsymbol{I}(\boldsymbol{q}1,2 \geq \boldsymbol{\nu}1,2)) \\ \vdots \\ \boldsymbol{Y}_t(I(\boldsymbol{q1,2} < \boldsymbol{\nu}1,2)) \end{pmatrix} \tag{4}$$

By including the other non-threshold variables to Equation 4, we have:

$$R_{i_t} = \left[\beta_0 + \beta_1 Y_t(\nu 1,2) + \left(\sum_{n=i}^{m} \beta_n Y_{t-n}\right) + \epsilon_{i_t}\right] \tag{5}$$

Equations 2–5 describe the relationship between the dependent variable and its explanatory variables, distributed by the values of threshold variables ($q1$ and $q2$) and given that the threshold variables are either larger or smaller than the threshold values (v1 and v2). In the separate equations, it is assumed that the threshold value is unknown, hence when q1 or q2 is greater than the threshold value v1 or v2, the resulting outcome suggests a significant impact of the shift in behaviour of the threshold variable. Furthermore, for efficient estimation of β_1 and β_2, the equation requires that elements of $q1$ and $q2$ are time variant and the error term ϵ_t is assumed to have a mean of zero and finite variance, thus independent and identically distributed.

4 | DATA

This study examines at industry level the relationship between sentiment-apt investors and stock returns in the UK. Data on returns covers aggregate monthly returns for each of the sectors from the period January 1988 to December 2017 and were sourced based on the Datastream Industry Classification Benchmark (ICB). The UK market, according to the classification, is grouped into 10 sectors with the following number of firms: Oil and Gas (13); Basic Materials (25); Industrials (105); Consumer Goods (43); Healthcare (18); Consumer Services (86); Telecoms (6); Utilities (8); Financials (306); and Technology (16). The sentiment variables used in the study are (i) the ratio of laggards to leaders and (ii) the growth opportunity index while other independent variables include the dividend yield, the price to book ratio, the price to earnings ratio, the size and liquidity, for each of the sectors. Our independent variables follow the approach of Baker and Wurgler (2007) and in conjunction with the sentiment variables, they are calculated from data obtained from Datastream. Table 1 shows the definition of variables used in our study.

TABLE 1 Definitions of variables

Variable	Definition	Measurement
R_t	Monthly returns index of each sector	$\text{Returns}_t = (P_t - P_{t-1})/P_{t-1}$
GRO	Growth opportunity index	Total capital expenditure divided by total assets in the sector
LagLead	Ratio of laggards to leaders	Total number of stocks advancing divided by number of stocks declining in prices
DY	Dividend yield	Dividend expressed as a percentage of share price at the end of each month, for each sector
PBR	Price to book ratio	Market value of total listed stocks of each sector divided by their book value
PER	Price to earnings ratio	Market value of total listed stocks of each sector divided by their book value
SIZ	Size	Natural logarithm of total assets of each sector
LIQ	Liquidity	Natural logarithm of total volume of trade for each sector

5 | EMPIRICAL FINDINGS

5.1 | Descriptive statistics & empirical results

The empirical analysis begins with the descriptive statistics. Table 2 includes the statistics of both dependent and independent variables. As can be seen from Table 2, the average of returns for the oil and gas sector (4.42) is the highest among all the sectors while that of the utilities sector (3.13) is the lowest within the same sample period. This implies that investors in the oil and gas sector have earned more average returns in the market than investors in other sectors of the market. Bearing in mind the highly volatile state of prices of oil in the international market, it is not surprising to observe that investors in the sector would earn a premium over other sectors' returns. Furthermore, in terms of the growth opportunity index (GRO), the oil and gas sector also has the highest average growth opportunity (9%) of all the sectors, while the financial sector reports the lowest (0.003). Based on our computation of GRO, the figure suggests that within the sample period, the oil and gas sector invested hugely in capital projects compared to other sectors. This is clearly tenable given the capital intensive nature of the oil and gas sector. The fact that the financial sector has the lowest growth opportunity index underscores the peculiarity of the sector. Loans and advances are the major productive assets of the financial sector and do not form part of their capital expenditure in the financial statement, as used in our computation. At the same time, the financial sector has the highest ratio of laggards to leaders (3.09) within the sample period. This implies that on average, in comparison with stocks appreciation, the financial sector witnessed the depreciation of more stocks in a current month relative to the previous month. To a large extent, this result is, perhaps, a reflection of the impact of the

TABLE 2 Descriptive statistics

Variable	Mean	Median	*SD*	Min	Max	Skewness	Kurtosis
Panel A: OIL AND GAS SECTOR							
R_t	4.42	4.48	0.38	3.64	4.95	−0.51	1.95
GRO	0.09	0.09	0.02	2.32	7.81	0.06	2.12
LagLead	2.16	2.17	0.21	1.71	2.53	−0.13	1.79
DY	4.14	3.72	1.25	2.32	7.81	0.75	2.57
PBR	1.98	1.80	0.77	0.83	4.39	0.68	2.83
PER	13.42	13.82	4.04	5.93	29.03	0.71	4.09
SIZ	8.18	8.29	0.41	7.43	8.75	−0.55	2.09
LLIQ	6.09	6.18	0.38	5.28	6.79	−0.39	2.07
Panel B: BASIC MATERIALS							
R_t	3.93	3.84	0.33	3.30	4.51	0.09	1.65
GRO	0.07	0.07	0.02	0.04	0.11	0.15	2.17
LagLead	2.53	2.54	0.13	2.18	2.89	−0.21	2.68
DY	3.74	3.93	1.05	0.93	7.47	−0.03	2.41
PBR	2.13	2.06	0.6	0.64	4.53	0.90	4.55
PER	12.38	12.18	3.06	4.49	4.53	0.44	3.51
SIZ	7.72	7.75	0.57	6.76	8.56	0.03	1.71
LLIQ	6.16	6.18	0.23	5.44	6.63	−0.66	3.30
Panel C: INDUSTRIALS							
R_t	4.10	4.09	0.35	3.39	4.75	−0.02	2.09
GRO	0.05	0.04	1.03	1.97	6.51	0.41	2.32
LagLead	2.70	2.59	0.01	0.02	0.08	0.22	1.44
DY	3.40	3.18	1.03	1.97	6.51	0.93	3.16
PBR	2.50	2.51	0.79	0.97	4.33	−0.06	2.29
PER	13.38	13.76	2.63	7.27	19.85	−0.46	2.50
SIZ	7.82	7.85	0.35	7.04	8.38	−0.12	1.71
LLIQ	6.20	6.26	0.32	5.50	6.90	−0.14	2.22
Panel D: CONSUMER GOODS							
R_t	3.64	3.61	0.40	2.93	4.41	0.16	2.11
GRO	0.03	0.03	0.01	0.02	0.06	1.64	4.91
LagLead	2.08	1.90	0.40	1.43	2.69	0.24	1.37
DY	3.84	3.39	1.34	1.36	8.70	1.12	4.24
PBR	3.47	3.44	1.01	1.49	7.79	0.82	4.78
PER	13.21	12.98	2.29	7.80	18.21	0.07	2.74
SIZ	7.98	7.97	0.23	7.43	8.41	−0.38	2.63
LLIQ	5.51	5.31	0.59	4.51	6.57	0.26	1.57
Variable	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**Skewness**	**Kutosis**
Panel E: HEALTHCARE							
R_t	4.40	4.51	0.36	3.63	5.03	−0.42	2.36
GRO	0.05	0.05	0.02	2.17	5.22	0.13	1.78
LagLead	0.05	0.05	0.02	0.02	0.09	−0.31	2.22
DY	3.61	3.70	0.67	2.17	5.22	−0.17	2.19
PBR	6.15	5.79	2.02	3.51	12.81	1.32	4.40

TABLE 2 (Continued)

PER	16.26	15.36	5.69	7.98	35.55	1.16	3.76
SIZ	7.21	7.58	0.79	5.79	8.28	−0.60	1.93
LLIQ	5.98	5.96	0.32	5.34	6.71	0.28	2.05
Panel F: CONSUMER SERVICES							
R_t	4.07	4.12	0.27	3.47	4.52	−0.44	2.47
GRO	0.07	0.07	0.03	0.03	0.13	0.87	2.91
LagLead	2.96	2.95	0.13	2.59	3.29	0.17	2.76
DY	3.08	2.87	0.64	2.10	5.24	0.95	3.31
PBR	2.35	2.39	0.47	1.31	3.46	0.01	2.13
PER	14	14.14	2.18	9.80	18.77	0.01	2.18
SIZ	7.96	8.03	0.41	7.11	8.53	−0.31	1.74
LLIQ	6.56	6.58	0.36	5.76	7.23	−0.29	2.29
Panel G: TELECOMS							
R_t	3.59	3.60	0.32	2.88	4.09	−0.28	2.16
GRO	0.08	0.06	0.04	0.73	7.20	0.57	1.84
LagLead	1.79	1.86	0.23	1.11	2.24	−0.74	2.73
DY	3.78	4.11	1.44	0.73	7.20	−0.51	2.49
PBR	−0.97	3.63	27.3	−268.58	10.51	−6.71	53.50
PER	16.13	13.12	1.91	7.69	53.94	1.92	6.55
SIZ	7.86	8.13	0.43	7.20	8.37	−0.36	1.24
LLIQ	6.22	6.31	0.63	4.86	7.26	−0.24	1.84
Panel H: UTILITIES							
R_t	3.13	3.06	0.39	2.31	3.72	−0.25	1.96
GRO	0.08	0.07	0.03	0.04	7.40	1.38	3.87
LagLead	2.03	2.05	0.14	1.67	2.34	−0.19	2.26
DY	4.95	4.95	0.81	3.03	7.40	0.28	3.07
PBR	2.41	2.59	0.96	0.56	4.58	−0.39	2.19
PER	11.56	12.26	3.28	2.64	17.47	−0.66	2.59
SIZ	7.59	7.75	0.46	6.66	8.15	−0.56	1.95
LLIQ	5.92	5.94	0.30	4.88	6.46	−0.69	3.61
Variable	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**Skewness**	**Kutosis**
Panel I: FINANCIAL							
R_t	4.23	4.38	0.35	3.42	4.63	−0.94	2.50
GRO	0.003	0.003	0.002	0.001	0.01	2.44	10.54
LagLead	3.09	3.13	0.22	2.57	3.48	−0.35	1.92
DY	3.97	3.68	1.15	2.45	12.00	1.88	10.09
PBR	1.31	1.25	0.38	0.46	2.28	0.21	2.36
PER	12.22	11.85	2.51	6.69	20.40	0.60	3.33
SIZ	9.28	9.34	0.53	8.32	9.91	−0.34	1.74
LLIQ	6.56	6.78	0.51	5.31	7.27	−0.71	2.32
Panel J: TECHNOLOGY							
R_t	3.95	3.90	0.40	3.20	4.83	−0.01	2.17
GRO	0.05	0.03	0.04	0.01	0.12	0.54	1.51
LagLead	2.25	2.32	0.28	1.43	2.87	−0.62	2.95

(Continues)

TABLE 2 (Continued)

DY	1.32	1.31	0.19	0.25	3.03	0.18	3.16
PBR	5.05	3.94	3.63	1.34	22.40	2.05	7.48
PER	18.35	16.44	9.32	8.89	81.08	3.91	21.77
SIZ	6.25	6.49	0.54	5.24	7.30	−0.53	1.84
LLIQ	5.4	5.68	0.95	0.00	6.65	−1.58	6.82

Note: This table shows the descriptive statistics of variables adopted in the study and data covers the period from January 1988 to December 2017.

2007 global financial crisis on financial sectors across the world. Also included in the descriptive statistics are the results of skewness and kurtosis normality tests. The outputs show that many of the variables deviate from normal distribution.

Table 3 shows the results of the pairwise correlation matrix. Across all sectors, the variables are reported to have a statistically significant relationship with each other, except in a few cases. Furthermore, while some sectors report reasonably low coefficients among the independent variables, other sectors reveal a high correlation among the independent variables. Of particular concern is the correlation coefficient between the two sentiment variables (ratio of laggards to leaders and growth),where the correlation coefficient is also high. This might pose a multi-colinearity problem, and to avoid this, in our threshold regression estimates, both variables are isolated as separate threshold variables rather than estimating them concurrently.

Given the non-stationarity nature of most time series data, the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity tests were conducted to ensure that variables used for this study are devoid of unit root. In principle, the ADF and PP statistics for all variables should be negative, whereas the KPSS should be positive; hence, the null hypothesis of non-stationarity is rejected if the computed t (tau) statistic (for ADF and PP) is more negative than the critical value at any particular point in time. The ADF tests are based on a maximum of 16 lags differences as determined by the Akaike Information Criterion (AIC), while the Newey-West procedure is used to calculate bandwidths for the PP and KPSS tests. In addition, Bertlett's Kernel is used for spectral estimation. The output of the unit root test (as shown in Table 4) suggests stationarity of variables at level and/or first difference.

Table 5 shows the empirical findings of the OLS regression. Following McMillan (2001), for each of the regressors, we begin with a lag length of five, and systematically eliminate the lags as they become statistically significant based on the information criteria, hence eventually retaining their contemporaneous form. Table 5 reports the linear regression results for all sectors. For the first sentiment variable (ratio of laggards to leaders), we propose that an increase in this variable will lead to a decrease in the overall sectoral return. In view of this proposition, using the linear regression estimate, three sectors significantly conform to our hypothesis, while others have a significant positive relationship. The three sectors that significantly conform are basic materials(−0.04*), healthcare(−0.20***) and utilities(−0.11***) sectors.[5] Their negatively signed coefficients suggest that an increase in the proportion of laggards to leading stocks results in a decrease in the overall return of those sectors.

In the case of the second sentiment variable (growth opportunity index), we hypothesize that an increase in this variable will propel an increase in overall sectoral returns. The result of the growth opportunity index has a significant impact on the overall return indices of industrials (3.11***), consumer goods (11.88***), utilities (0.96***), financials (4.65**) and technology (6.69***) sectors, although it has no significant impact on overall returns in four sectors (oil & gas, healthcare, consumer services and telecoms). Furthermore, despite the significant impact of the sentiment variable in the basic material sector, its negatively signed coefficient (−0.81***) does not conform with our hypothesis. In our opinion, its nonconformity is, perhaps, due to the sensitivity of the sector to business cycles, such as fluctuations in purchasing power. Most firms in this sector rely heavily on a vibrant economy, and their activities often involve extraction and supply of raw materials for construction purposes. Other independent variables, such as dividend yield, PB ratio, PE ratio and size and liquidity, also reveal a significant impact on sectoral returns at different levels of significance. Our results conform with the earlier position of similar findings on investor sentiment such as Baker and Wurgler (2007); Huang et al. (2008); Bekiros et al. (2016) and Yang et al. (2017).

Our preliminary regression suggests that across the sectors, a mixture of significant positive and negative relationships exist between the dependent variable and the sentiment variables. Shifting attention to a non-linear estimation, we employ a threshold regression model to

TABLE 3 Correlation matrix of variables

Variable	R_t	GRO	LagLead	DY	PBR	PER	SIZ	LLIQ
Panel A: OIL AND GAS SECTOR								
Rt	1.00							
GRO	−0.63***	1.00						
LagLead	0.83***	−0.42***	1.00					
DY	−0.23***	0.29***	−0.16***	1.00				
PBR	−0.09*	0.01	−0.20***	−0.69***	1.00			
PER	−0.22***	0.07	−0.47***	−0.13***	0.60***	1.00		
SIZ	0.97***	−0.67***	0.81***	−0.18***	−0.16***	−0.25***	1.00	
LLIQ	0.76***	−0.62***	0.70***	−0.44***	0.24***	0.20	0.74***	1.00
Panel B: BASIC MATERIALS								
R_t	1.00							
GRO	0.64***	1.00						
LagLead	−0.54***	−0.26***	1.00					
DY	−0.84***	−0.56***	0.50***	1.00				
PBR	0.15***	0.24***	−0.18***	−0.40***	1.00			
PER	−0.10*	−0.20***	0.10**	0.14****	−0.07	1.00		
SIZ	0.93***	0.61***	−0.45***	−0.65***	−0.14***	−0.03	1.00	
LLIQ	0.59***	0.44***	−0.21***	−0.43***	0.08	0.27***	0.66***	1.00
Panel C: INDUSTRIALS								
R_t	1.00							
GRO	−0.82***	1.00						
LagLead	0.80***	−0.67***	1.00					
DY	−0.79***	0.61***	−0.64***	1.00				
PBR	0.66***	−0.53***	0.41***	−0.72***	1.00			
PER	0.46***	−0.26***	0.11**	−0.56***	0.57***	1.00		
SIZ	0.94***	−0.87***	0.81***	−0.61***	0.55***	0.23***	1.00	
LLIQ	0.68***	−0.62***	0.59***	−0.46***	0.59***	0.20***	0.77***	1.00
Panel D: CONSUMER GOODS								
R_t	1.00							
GRO	−0.72***	1.00						
LagLead	0.83***	−0.54***	1.00					
DY	−0.70***	0.56***	−0.50***	1.00				
PBR	0.61***	−0.54***	0.40***	−0.56***	1.00			
PER	0.75***	−0.59***	0.57***	−0.58***	0.78***	1.00		
SIZ	0.94***	−0.86***	0.78***	−0.59***	0.59***	0.73***	1.00	
LLIQ	0.85***	−0.68***	0.93***	−0.56***	0.43***	0.57***	0.82***	1.00
Panel E: HEALTHCARE								
R_t	1.00							
GRO	−0.76***	1.00						
LagLead	−0.45***	0.74***	1.00					
DY	−0.15***	−0.33***	−0.54***	1.00				
PBR	−0.04	0.48***	0.58***	−0.72***	1.00			
PER	0.01	0.54***	0.63***	−0.79***	0.76***	1.00		

(Continues)

TABLE 3 (Continued)

SIZ	0.95***	−0.77***	−0.44***	−0.06	−0.04	−0.13***	1.00	
LLIQ	−0.08	0.40***	0.78***	−0.66***	0.62***	0.55***	−0.01	1.00
Panel F: CONSUMER SERVICES								
R_t	1.00							
GRO	−0.93***	1.00						
LagLead	0.32***	−0.32***	1.00					
DY	−0.71***	0.59***	−0.42***	1.00				
PBR	0.34***	−0.15***	0.12**	−0.64***	1.00			
PER	0.32***	−0.17***	0.41***	−0.73***	0.81***	1.00		
SIZ	0.92***	−0.94***	0.30***	−0.47***	−0.03	0.03	1.00	
LLIQ	0.65***	−0.72***	0.69***	−0.53***	−0.01	0.32***	0.72***	1.00
Panel G: TELECOMS								
R_t	1.00							
GRO	−0.64***	1.00						
LagLead	0.74***	−0.74***	1.00					
DY	−0.08	0.04	−0.31***	1.00				
PBR	−0.01	0.13***	−0.15***	0.28***	1.00			
PER	0.52***	−0.13***	0.44***	−0.69***	−0.30***	1.00		
SIZ	0.69***	−0.95***	0.78***	−0.04	-0.15***	0.15***	1.00	
LLIQ	0.60***	−0.86***	0.84***	−0.31***	−0.17***	0.28***	0.88***	1.00
Panel H: UTILITIES								
R_t	1.00							
GRO	−0.79***	1.00						
LagLead	−0.44***	0.15***	1.00					
DY	−0.44***	0.37***	−0.21***	1.00				
PBR	0.78***	−0.79***	−0.08	−0.63***	1.00			
PER		0.79***	−0.72***	0.00	−0.67***	0.74***	1.00	
SIZ	0.97***	−0.86***	−0.38***	−0.39***	0.84***	0.77***	1.00	
LLIQ	0.36***	−0.61***	0.47***	−0.58***	0.68***	0.58***	0.47***	1.00
Panel I: FINANCIALS								
R_t	1.00							
GRO	−0.68***	1.00						
LagLead	0.80***	−0.59***	1.00					
DY	−0.55***	0.36***	−0.27***	1.00				
PBR	0.23***	0.03	−0.24***	−0.32***	1.00			
PER	0.13***	−0.17***	−0.17***	−0.41***	0.58***	1.00		
SIZ	0.90***	−0.72***	0.91***	−0.38***	−0.19***	−0.13***	1.00	
LLIQ	0.92***	−0.70***	0.87***	−0.33***	−0.03***	−0.05	0.95	1.00
Panel J: TECHNOLOGY								
R_t	1.00							
GRO	−0.42***	1.00						
LagLead	0.61***	−0.58***	1.00					
DY	−0.34***	−0.35***	−0.26***	1.00				
PBR		0.09	0.69***	−0.27***	−0.51***	1.00		

TABLE 3 (Continued)

PER	0.57***	0.16***	0.37***	−0.55***	0.28***	1.00		
SIZ	0.66***	−0.94***	0.69***	0.23***	−0.55***	0.03***	1.00	
LLIQ	0.54***	−0.70***	0.86***	−0.03	−0.36***	0.23***	0.79***	1.00

TABLE 4 Unit root test of variables

	Level			Differenced		
Variable	ADF	PP	KPSS	ADF	PP	KPSS
Panel A: OIL AND GAS SECTOR						
R_t	−1.53	−1.61	2.24	−20.99	−21.25	0.16
GRO	−2.40	−2.45	1.04	−18.83	−18.83	0.03
LagLead	−2.01	−3.99	1.98	−16.97	−64.70	0.27
DY	−2.17	−2.16	0.42	−16.14	−21.28	0.22
PBR	−2.13	−1.74	0.71	−15.55	−20.19	0.23
PER	−2.36	−2.31	0.56	−20.01	−20.12	0.09
Size	−1.29	−1.29	2.21	−19.00	−19.00	0.09
LLIQ	−1.87	−2.49	1.41	−20.18	−43.88	0.23
Panel B: BASIC MATERIALS						
R_t	−1.31	−1.38	2.21	−17.12	−17.12	0.04
GRO	−1.90	−1.92	1.22	−18.91	−18.91	0.13
LagLead	−3.20	−9.85	1.03	−16.72	−56.74	0.06
DY	−2.23	−2.35	1.42	−17.04	−16.96	0.03
PBR	−3.26	−3.25	0.29	−19.79	−20.10	0.07
PER	−3.36	−3.78	0.17	−17.92	−17.93	0.02
SIZ	−0.85	−0.89	2.34	−19.77	−20.13	0.10
LLIQ	−3.0376	−3.82	1.43	−6.19	−56.99	0.14
Panel C: INDUSTRIALS						
R_t	−0.99	−0.99	2.19	−16.99	−16.91	0.05
GRO	−0.94	−0.98	1.90	−18.58	−18.58	0.07
LagLead	−1.38	−2.37	1.81	−15.97	−42.84	0.13
DY	−2.43	−2.37	1.23	−16.89	−16.85	0.03
PBR	−2.63	−2.41	1.02	−21.20	−21.21	0.11
PER	−2.63	−2.71	0.32	−17.55	−17.53	0.06
SIZ	−1.95	−2.06	2.36	−19.80	−19.84	0.27
LLIQ	−1.63	−2.23	1.63	−6.70	−46.02	0.09
Panel D: CONSUMER GOODS						
R_t	−2.84	−2.70	1.08	−17.07	−16.99	0.03
GRO	−1.93	−1.94	1.50	−18.88	−18.88	0.04
LagLead	−1.37	−1.62	1.94	−18.98	−40.31	0.13
DY	−2.84	−2.70	1.08	−17.07	−16.99	0.03
PBR	−2.81	−2.88	0.96	−15.65	−18.32	0.08
PER	−2.88	−2.85	1.17	−15.69	−20.04	0.04
SIZ	−1.05	−1.05	2.10	−19.16	−19.16	0.07
LLIQ	−1.40	−1.41	2.01	−19.28	−30.10	0.06

(Continues)

TABLE 4 (Continued)

Panel E: HEALTHCARE						
R_t	−1.53	−1.61	2.24	−20.99	−21.25	0.16
GRO	−0.76	−0.76	1.91	−18.91	−18.91	0.14
LagLead	−1.91	−3.64	1.27	−16.31	−50.92	0.12
DY	−2.87	−2.48	0.29	−16.21	−21.72	0.07
PBR	−1.86	−1.99	0.46	−21.72	−21.75	0.11
PER	−1.85	−1.72	0.43	−20.90	−20.97	0.11
SIZ	−1.23	−1.23	2.19	−19.18	−19.19	0.09
LLIQ	−1.32	−1.99	0.60	−5.05	−34.68	0.13
Panel F: CONSUMER SERVICES						
R_t	−1.59	−1.59	2.03	−17.81	−17.78	0.12
GRO	−1.47	−1.47	2.07	−17.94	−17.92	0.10
LagLead	−2.63	−7.81	0.59	−17.62	−66.60	0.11
DY	−2.77	−2.98	0.72	−18.13	−18.12	0.03
PBR	−2.19	−2.18	0.19	−20.14	−20.14	0.06
PER	−2.78	−2.78	0.27	−20.12	−20.12	0.04
Size	−3.22	−3.56	2.34	−17.36	−17.31	1.00
LLIQ	−2.19	−1.62	1.31	−5.49	−43.21	0.20
Panel G: TELECOMS						
R_t	−1.82	−1.81	1.78	−18.28	−18.32	0.14
GRO	−1.56	−1.56	1.66	−18.92	−18.92	0.07
LagLead	−2.88	−3.59	1.42	−23.01	−55.11	0.15
DY	−1.38	−1.38	0.52	−18.89	−18.89	0.21
PBR	−4.56	−5.88	0.12	−18.68	−26.01	0.04
PER	−3.14	−1.92	0.22	−6.93	−20.58	0.10
Size	−1.41	−1.41	1.86	−18.97	−18.97	0.13
LLIQ	−1.46	−1.43	1.35	−17.53	−36.71	0.21
Panel H: UTILITIES						
R_t	−2.12	−1.94	2.13	−22.54	−22.35	0.25
GRO	−1.47	−1.47	1.47	−18.14	−18.14	0.08
LagLead	−2.03	−7.21	1.09	−17.49	−70.84	0.27
DY	−2.97	−2.91	0.46	−21.12	−21.05	0.10
PBR	−1.96	−1.89	1.44	−21.77	−22.14	0.35
PER	−2.53	−2.52	1.24	−20.25	−20.28	0.22
Size	−2.82	−3.13	2.10	−4.11	−19.72	0.77
LLIQ	−2.91	−3.87	0.63	−17.31	−45.59	0.40
Panel I: FINANCIALS						
R_t	−2.17	−2.14	1.87	−18.15	−18.17	0.27

(Continues)

TABLE 4 (Continued)

GRO	−3.86	−3.60	1.33	−15.62	−15.97	0.28
LagLead	−1.46	−4.24	2.25	−15.65	−81.08	0.18
DY	−3.78	−4.05	0.50	−6.73	−25.12	0.02
PBR	−2.61	−2.58	0.64	−19.37	−19.39	0.08
PER	−3.23	−3.35	0.28	−18.16	−18.15	0.04
Size	−2.02	−1.97	2.31	−4.20	−20.21	0.46
LLIQ	−2.93	−1.83	2.08	−6.29	−44.86	0.31
Panel J: TECHNOLOGY						
R_t	−1.18	−1.19	1.26	−15.05	−15.43	0.11
GRO	−0.77	−0.79	1.98	−18.45	−18.44	0.10
LagLead	−1.86	−2.85	1.28	−16.88	−44.98	0.22
DY	−2.68	−2.76	0.41	−17.92	−17.90	0.04
PBR	−2.22	−2.60	0.62	−22.32	−22.31	0.07
PER	−3.13	−2.88	0.21	−16.54	−16.58	0.03
Size	−0.28	−0.28	2.23	−16.97	−16.97	0.09
LLIQ	−4.00	−1.56	1.43	−25.99	−42.37	0.31

Note: This table shows the unit root test for all variables in each sector. The Augmented Dickey-Fuller (ADF) tests are based on a maximum of 16 lags differences as determined by the Akaike Information Criterion (AIC) while the Newey-West procedure is used to calculate bandwidths for Phillips-Peron (PP) and Kwiatkwoski-Phillips-Schmidt-Shin (KPSS) tests. Also, Bertlett's kernel is used for spectral estimation. Data covers the period from January 1988 to December 2017.

explore further the empirical threshold-dependence of sectoral returns on the sentiment variables (ratio of laggards to leaders and growth opportunity index). In the models, both sentiment variables represent the threshold variables and are estimated separately as $q1$ and $q2$ respectively. Based on our hypothesis, the coefficient of $q1$ is expected to be significantly negatively signed, whereas $q2$ is expected to produce a significant positive sign.

Although the threshold value is unknown, nonetheless, using the posterior mean,[6] we hypothesize, first, that in a prescribed sector of the stock market, if the ratio of underperforming to over-performing stocks is increasing (i.e., ratio of laggards to leaders), sentiment-disposed investors would avoid such sectors and by implication, the overall return index of the sector would be negatively affected. This is given the fact that sentiment-prone investors are mostly risk-averse investors who are generally more concerned about loss minimization rather than return maximization. We also hypothesize, secondly, that investors' attitude towards each sector of the stock market is divergent. However, sector(s) with higher growth opportunities are not only attractive but also coveted by rational investors, thus resulting in the attitudes of investors towards some particular sectors converging. Hence, such sectors exert an influence on investors' psychology and in turn, create a significant impact on the overall sectoral return index.

Table 6 shows the first threshold regression results for all sectors. The threshold variable in this model is the ratio of laggards to leaders, while other independent variables constitute the non-threshold variables. Based on the output, the coefficients of the threshold variable for the six sectors conform with our hypothesis. This suggests that any increase above the threshold value will trigger a significant negative impact on the returns of the six sectors. Starting with the oil and gas sector, its result shows that for any increase in the ratio of laggards to leaders above the estimated threshold value of 2.23, the return of the sector will fall by −0.23**(0.11),[7] this being the coefficient of the threshold variable. For the industrial sector, its negatively signed coefficient of −0.25***(0.03) shows that an increase above its estimated threshold value of 2.97 will result in a one-quarter decline in aggregate stock returns of the sector. Furthermore, the consumer goods sector shows an estimated threshold value of 2.37. Hence, an increase above this value will result in a loss of −0.46***(0.07) of the sector's aggregate returns, this being the coefficient of its threshold variable. Again, the consumer services sector reports a threshold value of 2.98. With a threshold coefficient of −0.48***(0.04), this result shows that almost half of the sector's return would be a loss, should there be an increase above the threshold value. The utilities sector shows that an increase above the threshold value of 2.13 will result in a decline in the sector's return by about −0.06*(0.04) and lastly, the result from the financial sector shows that its estimated threshold value is 3.32. An increase above this figure will cause a drop in the sector's return by −0.08**(0.04).

From the above findings, it is evident that financial sector has the highest threshold value (3.32) among the six conforming sectors. This figure further corroborates our initial descriptive statistics that report the financial sector to have the highest mean ratio of laggards to leaders (3.09). By implication, for the six conforming sectors,[8] we postulate that when the proportion of lagging to leading stocks increases above the threshold point, investors in those sectors would embark on profit-taking, hence the aggregate returns for the sectors will fall. Apart from the threshold variable, other non-threshold variables in the model, such as the dividend yield, the PB ratio, the PE ratio and the size and liquidity also reveal significant impact on sectoral returns at different levels of significance. Our results are similar to those of Bandopadhyaya and Jones (2006); Baker and

TABLE 5 Linear regression between the dependent and explanatory variables

Variable/sectors	1	2	3	4	5	6	7	8	9	10
LagLead	0.26***	−0.04*	0.08***	0.08**	−0.2***	0.1***	0.47***	−0.11***	0.08***	0.04
S.E.	(0.05)	(0.02)	(0.02)	(0.04)	(0.05)	(0.02)	(0.06)	(0.04)	(0.03)	(0.05)
GRO	0.55	−0.81***	3.11***	11.88***	−0.50	0.1	0.42	0.96***	4.65**	6.69***
S.E.	(0.35)	(0.18)	(0.38)	(1.06)	(0.50)	(0.27)	(0.54)	(0.28)	(2.07)	(0.56)
DIV	−0.01	−0.05***	−0.08	−0.07***	−0.05***	−0.07***	0.09***	−0.06***	−0.03***	−0.16***
S.E.	(0.01)	(0.003)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.003)	(0.02)
PBR	0.02	0.11***	0.01**	0.003	−0.02***	0.15***	0.002***	−0.03***	0.32***	0.03***
S.E.	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
PER	0.003*	−0.001	0.02***	0.010***	0.01***	0.0001	0.03***	0.02***	0.002	0.01***
S.E.	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SIZ	0.81***	0.51***	0.92***	1.49***	0.44***	0.62***	0.43***	0.84***	0.49***	1.29***
S.E.	(0.02)	(0.01)	(0.02)	(0.06)	(0.01)	(0.02)	(0.06)	(0.02)	(0.03)	(0.04)
LLIQ	0.004	−0.13***	−0.16***	0.07***	−0.07***	−0.1***	−0.10***	−0.19***	0.11***	−0.16****
S.E.	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)	(0.02)	(0.02)	(0.01)
R^2	0.86	0.78	0.68	0.85	0.66	0.80	0.84	0.88	0.58	0.94
F-stat	1,191.68	2,477.96	2,580.99	1,048.01	1,198.06	3,128.62	257.33	2,108.29	2,104.81	726.98
Prob	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: This table presents linear regression results of Equation (1) for the effect of sentiment variables on sectoral return in UK stock market for the period January 1988–December 2017. Regression coefficients are estimated using ordinary least square that are robust to heteroscedasticity. *, ** and *** refer to 10%, 5% and 1% levels of significance respectively. Column 1 represents results for oil and gas sector, column 2 for basic materials, column 3 for industrials, column 4 for consumer goods, column 5 for healthcare, column 6 for consumer services, column 7 for telecoms, column 8 for utilities, column 9 for financials and column 10 for technology.

TABLE 6 Threshold regression—LagLead and growth as threshold variables

Variable/sectors	1	2	3	4	5	6	7	8	9	10
Panel A: Laggards to leading										
Threshold value	2.23	2.54	2.97	2.37	2.49	2.98	2.00	2.13	3.32	2.47
Threshold variable										
LagLead	−0.23**	0.23***	−0.25***	−0.46***	0.46***	−0.48***	0.53***	−0.06*	−0.28***	0.08**
S.E.	(0.11)	(0.04)	(0.03)	(0.07)	(0.06)	(0.04)	(0.06)	(0.04)	(0.05)	(0.04)
Non-threshold variables										
DIV	−0.03***	−0.05***	−0.08***	−0.06***	−0.02	−0.10***	0.09***	−0.02***	−0.03***	−0.01
S.E.	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.019)	(0.01)	(0.01)	(0.003)	(0.01)
PBR	−0.01	0.11***	0.01	0.08***	−0.02***	−0.003	0.001***	0.01	0.06***	0.02***
S.E.	(0.02)	(0.01)	(0.01)	(0.01)	(0.004)	(0.02)	(0.0002)	(0.01)	(0.01)	(0.002)
PER	0.01	−0.002	0.02***	−0.03***	0.01***	−0.01**	0.01***	0.01***	0.001	−0.002***
S.E	(0.003)	(0.001)	(0.002)	(0.01)	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)
SIZ	0.69***	0.50***	0.78***	0.59***	0.43***	0.82***	0.42***	0.68***	0.55***	0.70***
S.E.	(0.04)	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
LLIQ	−0.08**	−0.09***	−0.16***	0.24***	0.02	−0.03	−0.03	−0.10***	0.05**	−0.02**
S.E.	(0.04)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
Adj.R^2	0.86	0.75	0.78	0.67	0.83	0.76	0.75	0.61	0.74	0.78
Panel B: Growth opportunity										
Threshold value	0.11	0.09	0.03	0.03	0.05	0.08	0.08	0.06	0.004	0.06
Threshold variable										
GRO	−11.34**	−2.23***	6.24***	−22.75***	6.86***	1.20***	5.37***	1.42***	2.72**	1.12
S.E.	(1.24)	(0.38)	(0.97)	(2.66)	(1.33)	(0.54)	(0.97)	(0.47)	(2.72)	(0.26)
Non-threshold variables										
DIV	−0.04***	0.04***	−0.09***	−0.03***	0.12***	−0.07***	0.09***	−0.04***	−0.03***	−0.04***
S.E.	(0.01)	(0.004)	(0.006)	(0.006)	(0.01)	(0.01)	(0.009)	(0.007)	(0.004)	(0.01)
PBR	−0.06**	0.12***	0.02***	0.02*	0.001	−0.04**	0.001***	−0.05***	0.15***	0.01***
S.E.	(0.02)	(0.01)	(0.007)	(0.009)	(0.004)	(0.02)	(0.0003)	(0.009)	(0.02)	(0.002)
PER	−0.003	−0.004***	0.02***	−0.002	0.02***	0.004	0.01***	−0.002	−0.01***	−0.003***
S.E.	(0.004)	(0.001)	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.0006)
SIZ	0.67***	0.54***	0.49***	0.53***	0.44***	0.68***	0.35***	0.69***	0.31***	0.69***
S.E.	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)	(0.008)
LIQ	0.06	−0.02	0.04	0.17***	0.06***	−0.12***	0.15***	−0.07***	0.23***	0.03***
S.E.	(0.05)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)	(0.008)
Adj.R^2	0.72	0.65	0.88	0.66	0.73	0.60	0.85	0.61	0.84	0.57

Wurgler (2007); Bekiros et al. (2016) and Yang et al. (2017).

With regards to the results of the second sentiment variable[9] (growth opportunity index), the coefficients of the threshold variable for six sectors also conform with our hypothesis. Based on the output of the industrial sector, the coefficient of the threshold variable is 6.24*** (0.97) while its threshold value is 0.03. By implication, any increase in the growth opportunity index above 0.03 will result in an increase in the sector's aggregate return by 6.24. For the healthcare sector, its threshold value of 0.05 suggests that any increase above this value will stimulate an increase in return by 6.86***(1.33). Furthermore, the consumer services sector has a threshold value of 0.08 with a threshold coefficient of 1.20***(0.54). This implies that a marginal increase of returns in the sector will be recorded when growth rises above the threshold point. For the telecoms sector, this also has a threshold value of 0.08 but has a higher threshold coefficient of 5.37***(0.97); the utilities sector has a threshold value of 0.06 with a threshold coefficient of 1.42***(0.47) and the technology sector has a threshold value of 0.06 with a coefficient of 1.12***(0.26). Other sectors that do not conform with our hypothesis but have a significant negative coefficient are: the oil and gas (−11.34**)(0.11),[10] the basic materials (−2.23***)(0.09), the consumer goods (−22.75***)(0.03) and the financial sectors (−7.62***)(0.004). Again, in conformity with our earlier descriptive statistics, the oil and gas and the financial sectors have the highest and lowest threshold value, respectively. This is in spite of their negatively signed coefficient. We posit that the negatively signed coefficient of these sectors demonstrates the apathy of investors towards excessive growth. This is, perhaps, because firms with a growth potential systematically retain part of their yearly profits for future capital expenditure. This corporate action may not be endured by some investors, particularly those who are dividend-oriented. Other non-threshold variables in the model, such as the dividend yield, the PB ratio, the PE ratio and the size and liquidity also reveal significant impact on sectoral returns at different levels of significance.

5.2 | Robustness checks

As a robustness test, we separate the whole sample periods into pre, during and post-global financial crisis (GFC) of 2007/2008. Consequently, we re-estimate the predictability of sentiment variables on sectoral returns for each of these sub-samples. Table 7 presents the results for the period of the GFC, Table 8 shows the results for the period of pre-GFC and Table 9 presents the results for the post-GFC. Generally, in the sub-sample periods, we observe that the two sentiment variables have a significant influence in many of the sectors, particularly during the financial crisis sub-sample period, although the coefficient of some of the variables report opposite signs when compared with the full sample period. Therefore, we interpret our results for these tables in a similar fashion as for the earlier obtained results. A graphical representation of variables for the sub-sample periods is shown in Figures 3–5.

We observe that during the sub-sample periods, sentiments relating to healthcare, utilities and technology sectors do not have the predictive power to explain returns in those sectors compared to the full sample period. However, results for the oil and gas sector and the financial sector become more significant for the GFC sample subperiod than for the other periods. We infer from these results that investors in both sectors reacted strongly to the sub-prime crisis which ravaged several stock markets in the world. Based on our findings, we submit that our results are consistent with previous studies, and acknowledge that the predictive ability of sentiments on asset returns is suitably measured and understood using nonlinear models, as have been used in previous studies (e.g., McMillan, 2001; Chu et al., 2016; Salhin et al., 2016).

6 | CONCLUSION

Previous studies into investor sentiment have focused mostly on aggregate market returns with an emphasis on predefined sentiment variables. To complement such research, this study makes important contributions to existing literature in two ways. First, we examined the role of sentiment-apt investors in influencing the overall return index of all sectors in the UK market from 1988 to 2017. Secondly, we established the importance of two sectoral level factors in predicting the returns of the sectors from both linear and nonlinear regression approaches. For the first sentiment variable (ratio of laggards to leading stocks), the study highlights the importance of the threshold value such that for any given sector, in a particular month when there is an increase in the proportion of laggards to leading stocks above the threshold value, investors in the sector would gradually embark on selloffs, which in turn affect the returns of the sector. For the second sentiment variable (growth opportunity index), the study observes that any increase above the growth threshold value means that the return for the sector will also increase. Other non-threshold variables in the models, such as the dividend yield, the PB ratio, the PE ratio, and the size and liquidity also show a significant

TABLE 7 Threshold regression: Global financial crisis period

Variable/sectors	1	2	3	4	5	6	7	8	9	10
Panel A: Laggards to leading										
Threshold value	0.15	0.38	0.93	0.37	0.01	0.89	0.10	0.13	0.97	0.74
Threshold variable										
LagLead	−0.10***	0.08**	−0.08*	0.06*	0.17	0.05**	0.03**	0.08	0.05***	−0.03
S.E.	(0.07)	(0.04)	(0.04)	(0.06)	(0.14)	(0.06)	(0.04)	(0.06)	(0.03)	(0.06)
Non-threshold variables										
DIV	−0.07***	−0.09***	−0.10***	−0.11***	−0.02***	−0.009	−0.09***	−0.03***	−0.07***	−0.13***
S.E.	(0.01)	(0.004)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
PBR	0.05**	0.09***	0.04*	−0.02	0.08***	0.10***	0.04	0.005	−0.02***	0.01
S.E.	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)
PER	−0.003	0.001	−0.003	0.02**	0.05***	−0.01*	0.002	0.01***	−0.002	0.01
S.E.	(0.01)	(0.001)	(0.01)	(0.01)	(0.01)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
SIZ	0.70***	0.47***	0.58***	0.48***	0.21***	0.52***	0.51***	0.47***	0.50***	0.63***
S.E.	(0.04)	(0.02)	(0.02)	(0.03)	(0.06)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)
LLIQ	−0.12**	0.03***	0.02	0.04	0.20***	0.01	0.005	−0.04*	−0.04***	−0.02
S.E.	(0.05)	(0.01)	(0.03)	(0.03)	(0.06)	(0.03)	(0.03)	(0.03)	(0.01)	(0.03)
Adj.R^2	0.84	0.75	0.58	0.76	0.83	0.60	0.55	0.71	0.64	0.77
Panel B: Growth opportunity										
Threshold value	0.42	0.05	0.01	0.07	0.04	0.08	0.02	0.13	0.32	0.07
Threshold variable										
GRO	1.44***	0.32	−3.44**	3.38*	19.86	2.72	−2.69***	−4.34	4.81***	−2.06
S.E.	(1.00)	(0.20)	(1.62)	(1.66)	(0.69)	(1.79)	(0.80)	(1.60)	(1.47)	(2.45)
Non-threshold variables										
DIV	−0.09***	−0.08***	−0.11***	−0.09***	−0.01***	0.01	−0.07***	−0.05***	−0.07***	−0.11***
S.E.	(0.02)	(0.004)	(0.006)	(0.01)	(0.004)	(0.03)	(0.005)	(0.008)	(0.005)	(0.01)
PBR	0.03	0.10***	0.02	−0.007	0.07***	0.11***	0.05***	0.003	−0.005	0.03
S.E.	(0.02)	(0.006)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.004)	(0.007)	(0.02)
PER	−0.004	0.0001	0.004	0.01**	0.04***	−0.01*	0.004**	0.007**	−0.004	0.01***
S.E.	(0.005)	(0.002)	(0.004)	(0.005)	(0.008)	(0.006)	(0.002)	(0.003)	(0.003)	(0.003)
SIZ	0.63***	0.50***	0.55***	0.45***	0.25***	0.53***	0.53***	0.46***	0.45***	0.60***
S.E.	(0.03)	(0.01))	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.02)
LLIQ	−0.07	0.02	0.03	0.04*	0.17***	−0.02	0.007	0.04	−0.02	−0.02
SE	(0.05)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.02)	(0.03)	(0.01)	(0.02)
Adj.R^2	0.75	0.64	0.58	0.62	0.68	0.50	0.75	0.61	0.74	0.70

TABLE 8 Threshold regression: Pre-global financial crisis

Variable/sectors	1	2	3	4	5	6	7	8	9	10
Panel A: Laggards to leading										
Threshold value	1.33	1.35	1.32	1.17	1.02	1.10	1.30	1.12	1.82	1.14
Threshold variable										
LagLead	0.17**	−0.16***	−0.21***	−0.13***	−0.13	0.17***	0.49***	0.16	−0.33**	0.62
S.E.	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.03)	(0.05)	0.03)	(0.05)	(0.07)
Non-threshold variables										
DIV	−0.04***	−0.05***	−0.06***	−0.08***	−0.08***	−0.08***	0.007	−0.08***	−0.06***	−0.25***
S.E.	(0.005)	(0.004)	(0.006)	(0.01)	(0.01)	(0.006)	(0.009)	(0.005)	(0.004)	(0.02)
PBR	0.13***	0.11***	0.03***	−0.03***	−0.03***	0.13***	0.0007***	0.07***	0.15***	0.02***
S.E.	(0.01)	(0.008)	(0.009)	(0.003)	(0.003)	(0.01)	(0.0002)	(0.01)	(0.02)	(0.002)
PER	−0.01***	−0.003**	0.02***	0.02***	0.02***	0.008***	0.02***	−0.0008	0.004***	0.01***
S.E.	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.0007)
SIZ	0.28***	0.30***	0.55***	0.33***	0.33***	0.44***	−0.22***	0.31***	0.43***	0.08*
S.E.	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.02)	(0.05)
LLIQ	0.27***	0.09***	0.02	0.04	0.04	−0.02	0.19***	0.07***	0.17***	0.05***
S.E.	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Adj.R^2	0.62	0.57	0.68	0.67	0.71	0.66	0.75	0.66	0.78	0.70
Panel B: Growth opportunity										
Threshold value	0.12	0.08	0.01	0.03	0.04	0.02	0.05	0.03	0.07	0.04
Threshold variable										
GRO	1.94**	9.53***	4.51***	7.28***	7.28	−0.81**	−1.06	3.54	−31.65**	−4.56
S.E.	(0.67)	(0.8)	(1.31)	(1.56)	(1.56)	(0.35)	(0.85)	(0.42)	(3.83)	(1.66)
Non-threshold variables										
DIV	−0.04***	−0.06***	−0.05***	0.08***	0.08***	−0.08***	−0.02**	−0.07***	−0.09***	−0.27***
S.E.	(0.007)	(0.003)	(0.005)	(0.02)	(0.02)	(0.006)	(0.01)	(0.004)	(0.004)	(0.02)
PBR	0.13***	0.08***	0.12***	−0.009*	−0.008*	0.06***	0.0007***	0.08***	0.22***	0.02***
S.E.	(0.009)	(0.007)	(0.009)	(0.005)	(0.005)	(0.01)	(0.0002)	(0.008)	(0.02)	(0.002)
PER	−0.006***	−0.003**	−3.73	0.02***	0.02***	0.01***	0.01***	0.0007	−0.003**	0.01***
S.E.	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.0008)
SIZ	0.36***	0.41***	0.29***	0.27***	0.27***	0.49***	0.25***	0.30***	0.28***	0.76***
S.E.	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.06)
LLIQ	0.20***	0.08***	0.21***	0.26***	0.26***	0.02	0.19***	0.03**	0.26***	0.03*
S.E.	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Adj.R^2	0.57	0.55	0.78	0.86	0.75	0.80	0.68	0.61	0.74	0.77

TABLE 9 Threshold regression: Post-global financial crisis

Variable/sectors	1	2	3	4	5	6	7	8	9	10
Panel A: Laggards to leading										
Threshold value	0.20	0.41	0.03	0.37	0.01	0.09	0.12	0.05	0.90	0.47
Threshold variable										
LagLead	−0.14**	−0.21***	−0.77***	−0.56***	−0.03	−0.05***	0.08	−0.07	0.26**	−0.04
S.E.	(0.05)	(0.05)	(0.15)	(0.15)	(0.04)	(0.02)	(0.09)	(0.04)	(0.09)	(0.09)
Non-threshold variables										
DIV	−0.03***	−0.05***	−0.04**	−0.06**	0.001	−0.06***	−0.04***	−0.03***	−0.02***	0.02
S.E.	(0.004)	(0.004)	(0.01)	(0.03)	(0.01)	(0.004)	(0.012)	(0.01)	(0.01)	(0.02)
PBR	0.04***	0.16***	−0.0008	−0.04***	0.02***	0.12***	−0.008	−0.02***	0.29***	0.10***
S.E.	(0.012)	(0.02)	(0.008)	(0.01)	(0.004)	(0.01)	(0.01)	(0.01)	(0.05)	(0.01)
PER	0.01***	−0.002	0.04***	0.06***	0.02***	−0.004**	0.01***	0.04***	0.01***	0.03***
S.E.	(0.002)	(0.001)	(0.003)	(0.005)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.01)
SIZ	0.70***	0.57***	0.99***	0.80***	0.64***	0.90***	−0.14	0.50***	1.37***	0.15
S.E.	(0.02)	(0.004)	(0.06)	(0.06)	(0.02)	(0.04)	(0.17)	(0.02)	(0.37)	(0.1)
LLIQ	−0.14***	−0.03	−0.29***	−0.29***	−0.11***	−0.07***	−0.36***	−0.11***	−0.22***	−0.14***
S.E.	(0.02)	(0.04)	(0.043)	(0.04)	(0.02)	(0.01)	(0.05)	(0.03)	(0.07)	(0.05)
Adj.R^2	0.57	0.62	0.78	0.69	0.71	0.60	0.56	0.71	0.68	0.61
Panel B: Growth opportunity										
Threshold value	0.53	0.14	0.27	0.04	0.32	0.47	0.10	0.33	0.24	0.19
Threshold variable										
GRO	0.53	−0.94	3.1	12.36***	2.20	−2.58***	−6.12***	2.20	−114.37*	−12.93
S.E.	(0.51)	(0.62)	(2.22)	(4.78)	(1.24)	(0.56)	(1.1)	(0.51)	(0.03)	(4.77)
Non-threshold variables										
DIV	−0.04***	−0.02***	−0.13***	−0.07**	−0.02***	−0.05***	−0.06***	−0.05***	0.01	0.01
S.E.	(0.003)	(0.005)	(0.02)	(0.03)	(0.01)	(0.005)	(0.01)	(0.01)	(0.01)	(0.02)
PBR	0.10***	0.26***	0.05***	−0.05***	0.03***	0.10***	−0.017***	−0.01	0.34***	0.11***
S.E.	(0.01)	(0.01)	(0.007)	(0.01)	(0.003)	(0.01)	(0.004)	(0.01)	(0.06)	(0.01)
PER	0.01***	−0.003**	0.004	0.07***	0.01***	0.001	0.015***	0.02***	0.02***	0.03***
S.E.	(0.001)	(0.001)	(0.004)	(0.01)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
SIZ	1.10***	0.49***	1.92***	0.59***	0.65***	0.90***	0.19	1.48***	0.56***	0.27***
S.E.	(0.09)	(0.02)	(0.1)	(0.05)	(0.013)	(0.04)	(0.15)	(0.11)	(0.04)	(0.08)
LLIQ	−0.05**	−0.01	−0.21***	−0.26***	−0.11***	−0.07***	−0.21***	−0.06***	−0.22***	−0.07*
S.E.	(0.02)	(0.03)	(0.03)	(0.05)	(0.02)	(0.01)	(0.05)	(0.02)	(0.06)	(0.04)
Adj.R^2	0.77	0.61	0.68	0.86	0.53	0.71	0.59	0.71	0.64	0.72

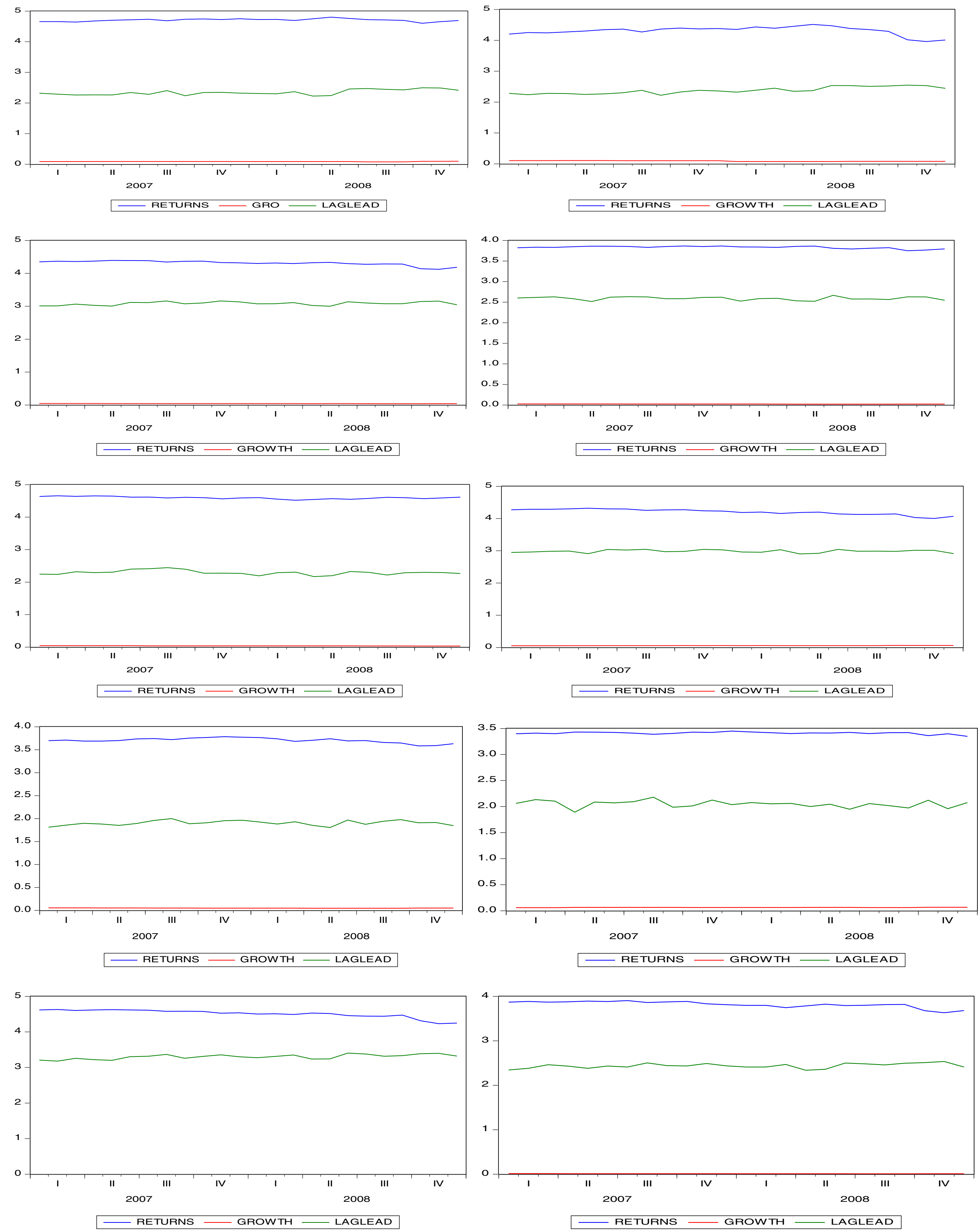

FIGURE 3 GFC sentiment indicators and sector groupings returns [Colour figure can be viewed at wileyonlinelibrary.com]

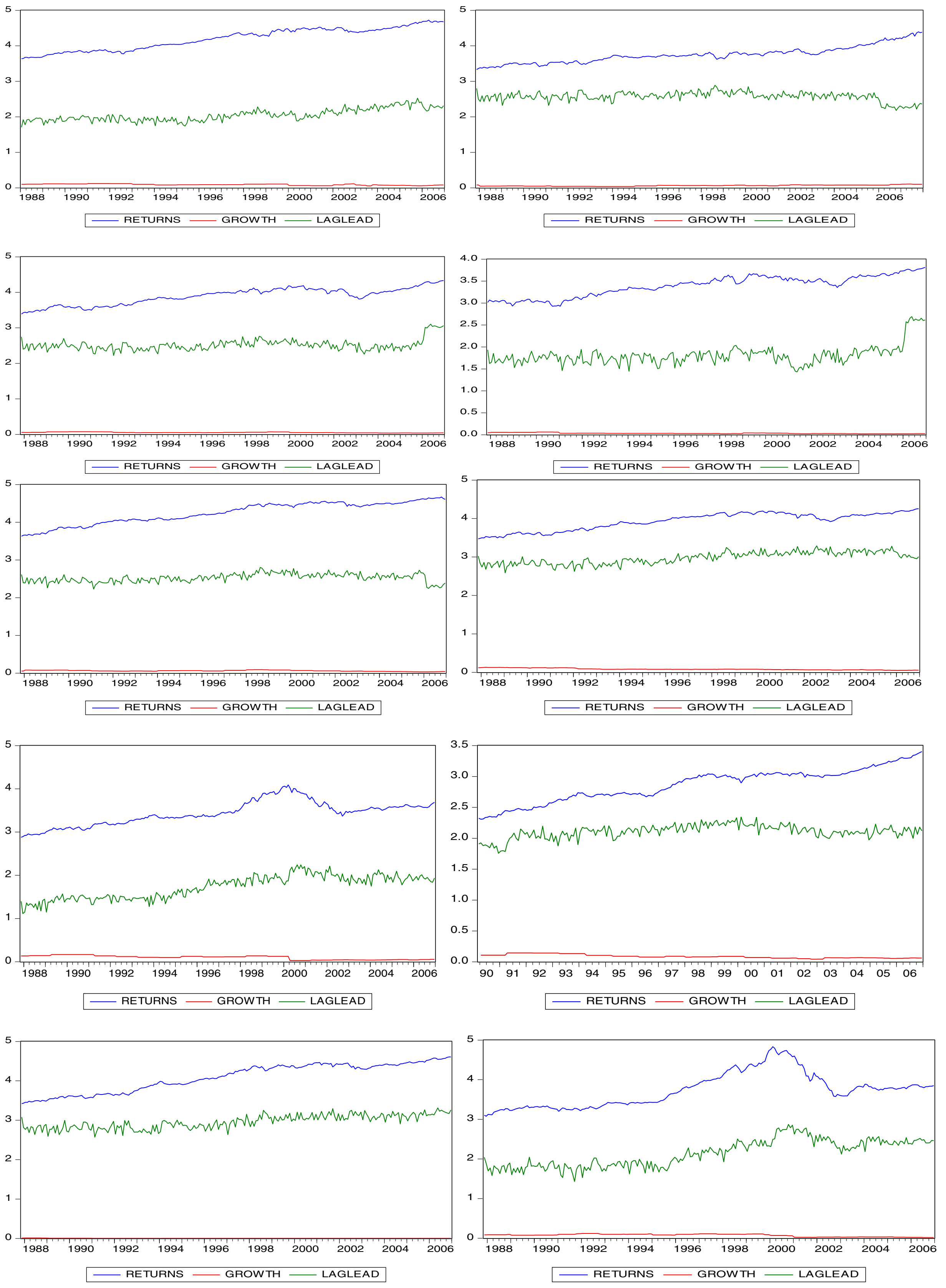

FIGURE 4 Pre-GFC sentiment indicators and sector groupings returns [Colour figure can be viewed at wileyonlinelibrary.com]

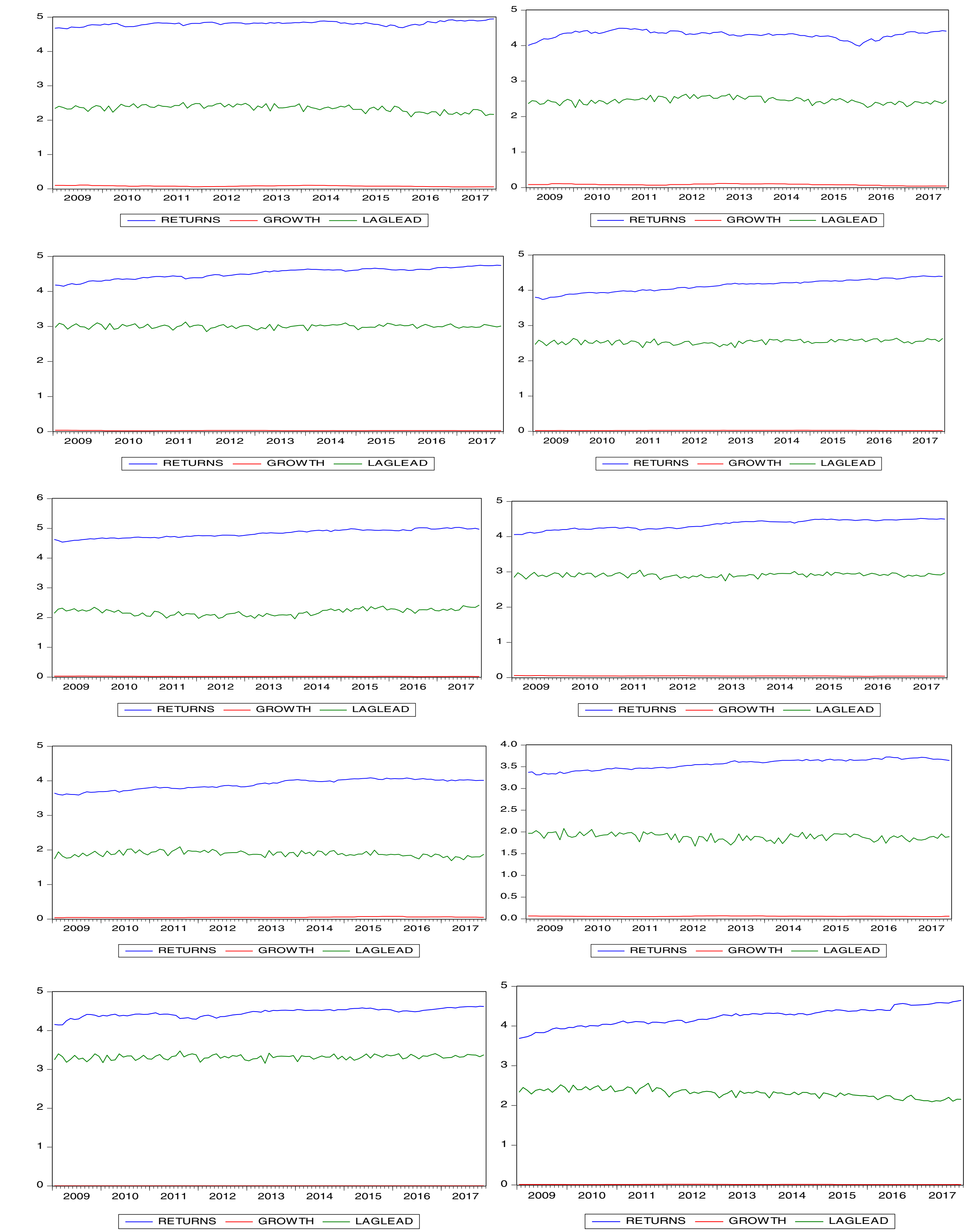

FIGURE 5 Post-GFC sentiment indicators and sector groupings returns [Colour figure can be viewed at wileyonlinelibrary.com]

impact on sectoral returns at different levels of significance.

The policy implications of our study are important. Given the developed state of the UK market, the findings that sentiment-disposed investors play significant roles in sectoral returns is highly noteworthy. A well-developed market such as the UK stock market is presumed to be almost close to being an efficient market; and thus the activities of a certain class of investors should have little or no significant impact on the return characteristic of any sector. This is due to the informational efficiency of such a developed market. However, in accordance with the results obtained, we posit that the UK stock market is mostly composed of risk-averse investors who are generally concerned more about risk or loss minimization rather than return maximization.

For future research, we suggest that other studies may build on this study to examine other areas not highlighted. For instance, they may address the role of sentiment-induced investors across markets rather than on a single market as in our case. Also, other studies may expand the sample period to account for other financial crises apart from the 2007/2008 GFC, as used in the present study.

ENDNOTES

[1] EMH is built on certain assumptions that have either been partly amended or nullified by some of the recent empirical studies in behavioural finance.

[2] The graphs presented in Figures 1 and 2 are further used to assess linearity of the variables in the methodology section.

[3] Garcia and Liu (1999) classified both Japan and United States as industrial economies while Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela, Indonesia, Korea, Malaysia, the Philippines, Taiwan and Thailand were classified as developing economies.

[4] See introductory part of this paper for some of the controversies surrounding the proxies.

[5] Figures in parenthesis represent the coefficient values of the linear regression estimate while *, ** and *** represent 10%, 5% & 1% significant levels respectively.

[6] The posterior mean is done by allowing the iteration process to allocate additional probability, in order to smoothen out the maximum likelihood estimate of the threshold values.

[7] Figures in parenthesis represent the standard error while *, ** and *** represent 10%, 5% & 1% significant levels respectively.

[8] Due to page constraint, we only interpret the results of the six sectors conforming with our hypothesis. However, results of other four non-conforming sectors (basic materials, healthcare, telecoms and technology) are reported in the threshold regression table. These sectors, in contrast to our hypothesis, report a threshold coefficient that is significantly positively signed.

[9] The results of the second threshold variable (growth opportunity index) are also reported in Table 6.

[10] Figures in the first parenthesis represent coefficient of threshold variable, figures in the second parenthesis represent threshold value while *, ** and *** represent 10%, 5% & 1% significant levels respectively.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Rilwan Sakariyahu https://orcid.org/0000-0001-7360-7434
Mohamed Sherif https://orcid.org/0000-0002-8670-672X
Audrey Paterson https://orcid.org/0000-0002-9157-8013
Eleni Chatzivgeri https://orcid.org/0000-0002-1833-1049

REFERENCES

Ahern, K. R., & Sosyura, D. (2015). Rumor has it: Sensationalism in financial media. *The Review of Financial Studies*, *28*(7), 2050–2093.

Ahmadi, F. (2016). The relationship between inflation and stock index in the last ten years, in Tehran stock exchange. *World Scientific News*, *40*, 34–57.

Akansu, A., Cicon, J., Ferris, S. P., & Sun, Y. (2017). Firm performance in the face of fear: How CEO moods affect firm performance. *Journal of Behavioral Finance*, *18*(4), 373–389.

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2013). Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quant- Itative Analysis*, *48*(1), 245–275.

Arabian, G., & Zomorrodian, R. (2007). Stock return, consumer confidence, purchasing manager's index and economic fluctuations. *Journal of Business and Economics Research*, *5*(8), 97–106.

Arin, K. P., Molchanov, A., & Reich, O. F. (2013). Politics, stock markets, and model uncertainty. *Empirical Economics*, *45*(1), 23–38.

Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets*, *7*(3), 271–299.

Baker, M., & Wurgler, J. (2004). Appearing and disappearing dividends: The link to catering incentives. *Journal of Financial Economics*, *73*(2), 271–288.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, *61*(4), 1645–1680.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, *21*(2), 129–152.

Bandopadhyaya, A., & Jones, A. L. (2006). Measuring investor sentiment in equity markets. *Journal of Asset Management*, *7*(3–4), 208–215.

Barber, B. M., & Odean, T. (2007). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, *21*(2), 785–818.

Bekiros, S., Gupta, R., & Kyei, C. (2016). A non-linear approach for predicting stock returns and volatility with the use of investor sentiment indices. *Applied Economics*, *48*(31), 2895–2898.

Ben-Rephael, A., Kandel, S., & Wohl, A. (2012). Measuring investor sentiment with mutual fund flows. *Journal of Financial Economics*, *104*(2), 363–382.

Bohl, M. T., & Henke, H. (2003). Trading volume and stock market volatility: The polish case. *International Review of Financial Analysis*, *12*(5), 513–525.

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1–8.

Bordino, I., Kourtellis, N., Laptev, N., & Billawala, Y. (2014). Stock trade volume prediction with yahoo finance user browsing behavior. In *30th international conference on data engineering (ICDE).* (pp. 1168–1173). Chicago, IL: IEEE.

Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near- term stock market. *Journal of Empirical Finance*, *11* (1), 1–27.

Brown, G. W., & Cliff, M. T. (2005). Investor sentiment and asset valuation. *The Journal of Business*, *78*(2), 405–440.

Campbell, J. Y., Giglio, S., Polk, C., & Turley, R. (2018). An intertemporal CAPM with stochastic volatility. *Journal of Financial Economics*, *128*(2), 207–233.

Chandra Pati, P., & Rajib, P. (2010). Volatility persistence and trading volume in an emerging futures market: Evidence from NSE nifty stock index futures. *The Journal of Risk Finance*, *11*(3), 296–309.

Chang, S.-C., Chen, S.-S., Chou, R. K., & Lin, Y.-H. (2012). Local sports sentiment and returns of locally headquartered stocks: A firm-level analysis. *Journal of Empirical Finance*, *19*(3), 309–318.

Chen, J., & Sherif, M. (2016). Illiquidity premium and expected stock returns in the UK: A new approach. *Physica A: Statistical Mechanics and its Applications*, *458*, 52–66.

Chen, M.-H. (2007). Macro and non-macro explanatory factors of Chinese hotel stock returns. *International Journal of Hospitality Management*, *26*(4), 991–1004.

Chen, N.-F., Kan, R., & Miller, M. H. (1993). Are the discounts on closed- end funds a sentiment index? *The Journal of Finance*, *48*(2), 795–800.

Chen, N.-F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business*, *59*(3), 383–403.

Chen, S.-S. (2011). Lack of consumer confidence and stock returns. *Journal of Empirical Finance*, *18*(2), 225–236.

Chen, S.-S. (2012). Revisiting the empirical linkages between stock returns and trading volume. *Journal of Banking and Finance*, *36*(6), 1781–1788.

Chiang, T. C., Qiao, Z., & Wong, W.-K. (2010). New evidence on the relation between return volatility and trading volume. *Journal of Forecasting*, *29*(5), 502–515.

Chopra, N., Lee, C. M., Shleifer, A., & Thaler, R. H. (1993). Yes, discounts on closed-end funds are a sentiment index. *The Journal of Finance*, *48*(2), 801–808.

Chordia, T., Subrahmanyam, A., & Anshuman, V. R. (2001). Trading activity and expected stock returns. *Journal of Financial Economics*, *59*(1), 3–32.

Chu, X., Wu, C., & Qiu, J. (2016). A nonlinear granger causality test between stock returns and investor sentiment for Chinese stock market: A wavelet-based approach. *Applied Economics*, *48*(21), 1915–1924.

Chung, S.-L., Hung, C.-H., & Yeh, C.-Y. (2012). When does investor sentiment predict stock returns? *Journal of Empirical Finance*, *19*(2), 217–240.

Cooper, M. J., Gutierrez, R. C., Jr., & Hameed, A. (2004). Market states and momentum. *The Journal of Finance*, *59*(3), 1345–1365.

Cornelli, F., Goldreich, D., & Ljungqvist, A. (2006). Investor sentiment and pre-IPO markets. *The Journal of Finance*, *61*(3), 1187–1216.

Corredor, P., Ferrer, E., & Santamaria, R. (2013). Investor sentiment effect in stock markets: Stock characteristics or country-specific factors? *International Review of Economics and Finance*, *27*, 572–591.

Cox, D. R., & Peterson, D. R. (1994). Stock returns following large one- day declines: Evidence on short-term reversals and longer-term perform- ance. *The Journal of Finance*, *49*(1), 255–267.

Da, Z., Engelberg, J., & Gao, P. (2014). The sum of all FEARS investor sentiment and asset prices. *The Review of Financial Studies*, *28*(1), 1–32.

Dalika, N. K. (2014). Sentiment and returns: Analysis of investor sentiment in the south African market. *Investment Management and Financial Innovations*, *12*(2), 267–276.

David, G., & Sultan, J. (1998). Consumer confidence announcements: Do they matter? *Applied Financial Economics*, *8*(2), 155–166.

Dorn, D. (2009). Does sentiment drive the retail demand for IPOs? *Journal of Financial and Quantitative Analysis*, *44*(1), 85–108.

Dougal, C., Engelberg, J., Garcia, D., & Parsons, C. A. (2012). Journalists and the stock market. *The Review of Financial Studies*, *25*(3), 639–679.

Doukas, J. A., & Milonas, N. T. (2004). Investor sentiment and the closed- end fund puzzle: Out-of-sample evidence. *European Financial Management*, *10*(2), 235–266.

Drake, M. S., Roulstone, D. T., & Thornock, J. R. (2012). Investor in- formation demand: Evidence from google searches around earnings announcements. *Journal of Accounting Research*, *50* (4), 1001–1040.

Edmans, A., Garcia, D., & Norli, Ø. (2007). Sports sentiment and stock returns. *The Journal of Finance*, *62*(4), 1967–1998.

Epstein, L. G. (1999). A definition of uncertainty aversion. *The Review of Economic Studies*, *66*(3), 579–608.

Errunza, V., & Hogan, K. (1998). Macroeconomic determinants of European stock market volatility. *European Financial Management*, *4*(3), 361–377.

Essaddam, N., & Karagianis, J. M. (2014). Terrorism, country attributes, and the volatility of stock returns. *Research in International Business and Finance*, *31*, 87–100.

Feldman, T. (2010). A more predictive index of market sentiment. *Journal of Behavioral Finance*, *11*(4), 211–223.

Ferrer, E., Salaber, J., & Zalewska, A. (2016). Consumer confidence in- dices and stock markets' meltdowns. *The European Journal of Finance*, *22*(3), 195–220.

Finter, P., Niessen-Ruenzi, A., & Ruenzi, S. (2012). The impact of investor sentiment on the German stock market. *Zeitschrift für Betrieb- Swirtschaft*, *82*(2), 133–163.

Fisher, K. L., & Statman, M. (2000). Investor sentiment and stock returns. *Financial Analysts Journal*, *56*(2), 16–23.

Fisher, K. L., & Statman, M. (2003). Consumer confidence and stock returns. *Journal of Portfolio Management*, *30*(1), 115–127.

Flannery, M. J., & Protopapadakis, A. A. (2002). Macroeconomic factors do influence aggregate stock returns. *The Review of Financial Studies*, *15*(3), 751–782.

Freybote, J., & Seagraves, P. A. (2017). Heterogeneous investor sentiment and institutional real estate investments. *Real Estate Economics*, *45*(1), 154–176.

Gagnon, L., & Karolyi, G. A. (2009). Information, trading volume, and in- ternational stock return comovements: Evidence from cross-listed stocks. *Journal of Financial and Quantitative Analysis*, *44*(4), 953–986.

Garcia, V. F., & Liu, L. (1999). Macroeconomic determinants of stock market development. *Journal of Applied Economics*, *2*(1), 29–59.

Gârleanu, N., & Pedersen, L. H. (2018). Efficiently inefficient markets for assets and asset management. *The Journal of Finance*, *73*(4), 1663–1712.

Gervais, S., Kaniel, R., & Mingelgrin, D. H. (2001). The high-volume return premium. *The Journal of Finance*, *56*(3), 877–919.

Girard, E., & Biswas, R. (2007). Trading volume and market volatility: Developed versus emerging stock markets. *Financial Review*, *42*(3), 429–459.

Goetzmann, W. N., Kim, D., Kumar, A., & Wang, Q. (2014). Weather- induced mood, institutional investors, and stock returns. *The Review of Financial Studies*, *28*(1), 73–111.

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics*, *93*(2), 345–368.

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *The Journal of Finance*, *58*(3), 1009–1032.

Hsing, Y. (2011). The stock market and macroeconomic variables in a BRICS country and policy implications. *International Journal of Economics and Financial Issues*, *1*(1), 12–18.

Huang, B.-N., Hwang, M. J., & Yang, C. W. (2008). Causal relationship between energy consumption and GDP growth revisited: A dynamic panel data approach. *Ecological Economics*, *67*(1), 41–54.

Humpe, A., & Macmillan, P. (2009). Can macroeconomic variables ex- plain long-term stock market movements? A comparison of the US and Japan. *Applied Financial Economics*, *19*(2), 111–119.

Jansen, W. J., & Nahuis, N. J. (2003). The stock market and consumer confidence: European evidence. *Economics Letters*, *79*(1), 89–98.

Jiang, L., & Li, G. (2013). Investor sentiment and IPO pricing during pre- market and aftermarket periods: Evidence from Hong Kong. *Pacific-Basin Finance Journal*, *23*(3), 65–82.

Kang, J., Liu, M.-H., & Ni, S. X. (2002). Contrarian and momentum strategies in the China stock market: 1993–2000. *Pacific-Basin Finance Journal*, *10*(3), 243–265.

Kasman, S., Vardar, G., & Tunç, G. (2011). The impact of interest rate and exchange rate volatility on banks' stock returns and volatility: Evidence from Turkey. *Economic Modelling*, *28*(3), 1328–1334.

Kearney, C., & Daly, K. (1998). The causes of stock market volatility in Australia. *Applied Financial Economics*, *8*(6), 597–605.

Kim, S.-H., & Kim, D. (2014). Investor sentiment from internet message postings and the predictability of stock returns. *Journal of Economic Behavior and Organization*, *107*, 708–729.

Larson, S. J., & Madura, J. (2003). What drives stock price behavior following extreme one-day returns. *Journal of Financial Research*, *26*(1), 113–127.

Lee, B.-S., & Rui, O. M. (2002). The dynamic relationship between stock returns and trading volume: Domestic and cross-country evidence. *Journal of Banking and Finance*, *26*(1), 51–78.

Lee, C. F., & Rui, O. M. (2000). Does trading volume contain information to predict stock returns? Evidence from China's stock markets. *Review of Quantitative Finance and Accounting*, *14*(4), 341–360.

Lee, C. M., Shleifer, A., & Thaler, R. H. (1991). Investor sentiment and the closed-end fund puzzle. *The Journal of Finance*, *46*(1), 75–109.

Lee, M., & Gan, C. (2006). Macroeconomic variables and stock market in- teractions: New Zealand evidence. *Investment Management and Financial Innovations*, *3*(4), 89–101.

Leitch, D., & Sherif, M. (2017). Twitter mood, ceo succession announcements and stock returns. *Journal of Computational Science*, *2*(1), 1–10.

Lemmon, M., & Portniaguina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *The Review of Financial Studies*, *19*(4), 1499–1529.

Levy, T., & Yagil, J. (2011). Air pollution and stock returns in the US. *Journal of Economic Psychology*, *32*(3), 374–383.

Lowry, M. (2003). Why does initial public offering volume fluctuate so much? *Journal of Financial Economics*, *67*(1), 3–40.

Lux, T. (2011). Sentiment dynamics and stock returns: The case of the German stock market. *Empirical Economics*, *41*(3), 663–679.

Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417.

McMillan, D. G. (2001). Nonlinear predictability of stock market returns: Evidence from nonparametric and threshold models. *International Review of Economics and Finance*, *10*(4), 353–368.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, *42*(3), 483–510.

Mostafa, M. M. (2013). More than words: Social networks' text mining for consumer brand sentiments. *Expert Systems with Applications*, *40*(10), 4241–4251.

Nofer, M., & Hinz, O. (2015). Using twitter to predict the stock market. *Business and Information Systems Engineering*, *57*(4), 229–242.

Oliveira, N., Cortez, P., & Areal, N. (2013). *On the predictability of stock market behavior using stocktwits sentiment and posting volume* (pp. 355–365). In: Portuguese Conference on Artificial Intelligence, Springer.

Olweny, T., & Omondi, K. (2011). The effect of macro-economic factors on stock return volatility in the Nairobi stock exchange, Kenya. *Economics and Finance Review*, *1*(10), 34–48.

O'Connor, A. J. (2013). The power of popularity: An empirical study of the relationship between social media fan counts and brand company stock prices. *Social Science Computer Review*, *31*(2), 229–235.

Patel, S. (2012). The effect of macroeconomic determinants on the performance of the Indian stock market. *NMIMS Management Review*, *22*(1), 117–127.

Patra, T., & Poshakwale, S. (2006). Economic variables and stock market returns: Evidence from the Athens stock exchange. *Applied Financial Economics*, *16*(13), 993–1005.

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial markets using google trends. *Scientific Reports*, *3*, 1684.

Ranco, G., Aleksovski, D., Caldarelli, G., Grčar, M., & Mozetič, I. (2015). The effects of twitter sentiment on stock price returns. *PLoS One*, *10*(9), e0138441.

Rao, T., and Srivastava, S., (2012). Analyzing stock market movements using twitter sentiment analysis. In: *Proceedings of the 2012 international conference on advances in social networks analysis and mining (ASONAM 2012)*. Istanbul, Turkey: IEEE Computer Society, pp. 119–123.

Ross, S. A. (1976). Arbitrage theory of capital asset pricing. *Journal of Economic Theory*, *13*(3), 341–360.

Salhin, A., Sherif, M., & Jones, E. (2016). Managerial sentiment, consumer confidence and sector returns. *International Review of Financial Analysis*, *47*(1), 24–38.

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance*, *16*(3), 394–408.

Scholtens, B., & Peenstra, W. (2009). Scoring on the stock exchange? The effect of football matches on stock market returns: An event study. *Applied Economics*, *41*(25), 3231–3237.

Sehgal, V., & Song, C. (2007). Sops: Stock prediction using web sentiment. In *Seventh IEEE international conference on Data mining workshops* (pp. 21–26). Omaha, Nebraska: IEEE.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*(3), 425–442.

Shefrin, H., & Statman, M. (2000). Behavioral portfolio theory. *Journal of Financial and Quantitative Analysis*, *35*(2), 127–151.

Sherif, M., & Chen, J. (2019). The quality of governance and momentum profits: International evidence. *The British Accounting Review*, *51*(5), 1–16.

Siganos, A., Vagenas-Nanos, E., & Verwijmeren, P. (2014). Facebook's daily sentiment and international stock markets. *Journal of Economic Behavior and Organization*, *107*(PB), 730–743.

Simões Vieira, E. (2011). Investor sentiment and the market reaction to dividend news: European evidence. *Managerial Finance*, *37*(12), 1213–1245.

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, *69*(1), 99–118.

Singer, E. (2002). The use of incentives to reduce nonresponse in household surveys. *Survey Nonresponse*, *51*(1), 163–177.

Smales, L. A. (2014). News sentiment and the investor fear gauge. *Finance Research Letters*, *11*(2), 122–130.

Takeda, F., & Wakao, T. (2014). Google search intensity and its relation- ship with returns and trading volume of Japanese stocks. *Pacific-Basin Finance Journal*, *27*, 1–18.

Tinbergen, J. (1939). *Business cycles in the United States of America: 1919–1932*. Geneva: League of Nations.

Tong, H. (1978). On a threshold model. *Journal of the Royal Statistical Society*, *42*, 245–292.

Tong, H., & Lim, K. S. (1980). Threshold autoregression, limit cycles and cyclical data. *Journal of the Royal Statistical Society. Series B (Methodological)*, *42*, 245–292.

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, *211*(4481), 453–458.

Uhl, M. W. (2014). Reuters sentiment and stock returns. *Journal of Behavioral Finance*, *15*(4), 287–298.

Wolfers, J. (2006). Diagnosing discrimination: Stock returns and CEO gender. *Journal of the European Economic Association*, *4* (2–3), 531–541.

Yang, H., Ryu, D., & Ryu, D. (2017). Investor sentiment, asset returns and firm characteristics: Evidence from the Korean stock market. *Investment Analysts Journal*, *46*(2), 132–147.

Yaya, O. S., & Shittu, O. I. (2010). On the impact of inflation and ex- change rate on conditional stock market volatility: A re-assessment. *American Journal of Scientific and Industrial Research*, *1*(2), 115–117.

Zakaria, Z., & Shamsuddin, S. (2012). Empirical evidence on the relationship between stock market volatility and macroeconomics volatility in Malaysia. *Journal of Business Studies Quarterly*, *4*(2), 61–71.

Zhang, X., Fuehres, H., & Gloor, P. A. (2011). Predicting stock market indicators through twitter "i hope it is not as bad as i fear". *Procedia-Social and Behavioral Sciences*, *26*(1), 55–62.

Zhang, Y., Zhang, Y., Shen, D., & Zhang, W. (2017). Investor sentiment and stock returns: Evidence from provincial tv audience rating in China. *Physica A: Statistical Mechanics and its Applications*, *466*(C), 288–294.

Zouaoui, M., Nouyrigat, G., & Beer, F. (2011). How does investor sentiment affect stock market crises? Evidence from panel data. *Financial Review*, *46*(4), 723–747.

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